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EMHIRES dataset
Part I: Wind power generation

European Meteorological derived HIgh resolution RES generation time series for present and future scenarios

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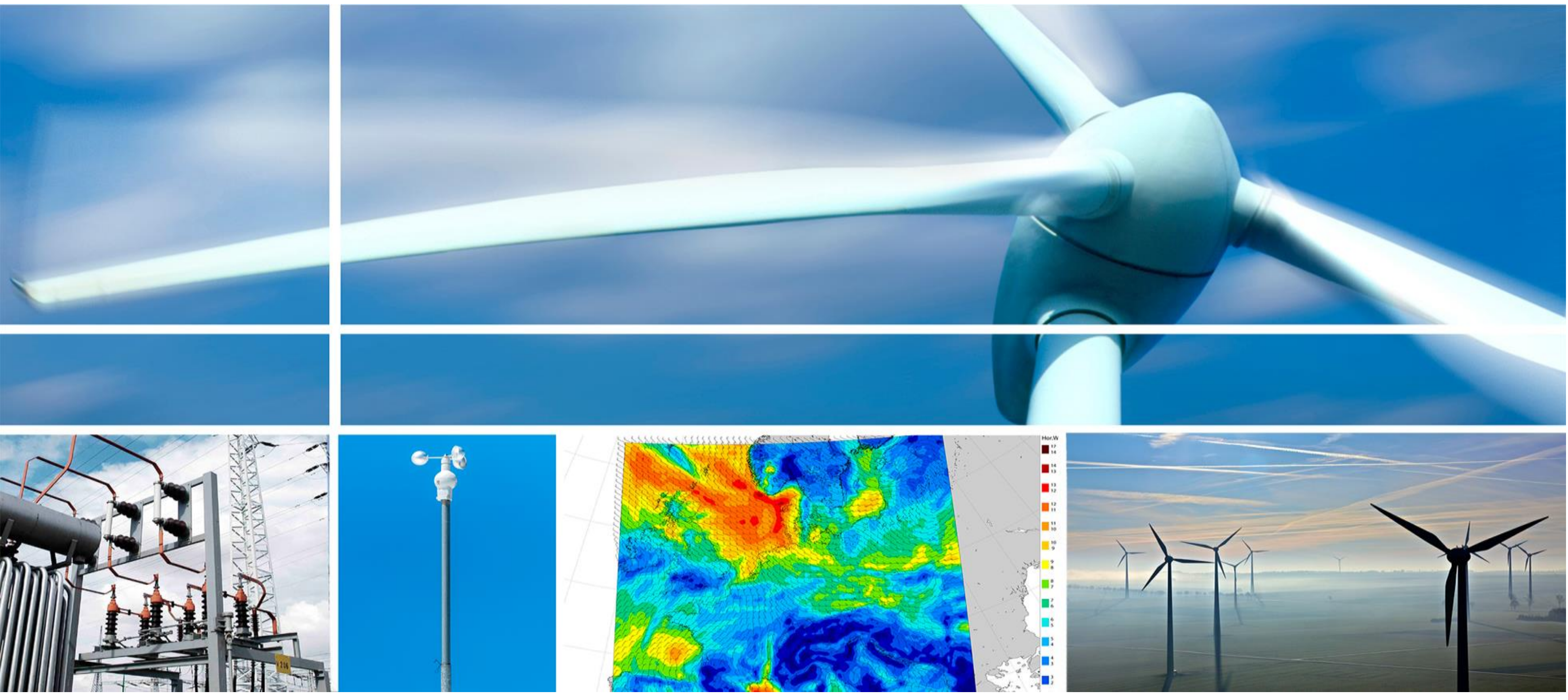

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Title
EMHIRES dataset: Wind power generation. European Meteorological derived HIgh resolution RES generation time series for present and future scenarios

Abstract
EMHIRES is the first publically available European wind power generation dataset derived from meteorological sources that is available on NUTS-2 level. It was generated applying an innovative methodology capturing local geographical information to generate meteorologically derived wind power time series at high temporal and spatial resolution. This allows for a better understanding of the wind resource at the precise location of wind farms.

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Executive summary

Renewable energy sources for the generation of electricity (RES-E) directly relates to three of the five pillars of the Energy Union: the fully integrated energy market, climate action and emission reduction as well as research and innovation [1]. The deployment of large capacities of wind and solar energy impacts the electricity markets and challenges existing market designs, both at the wholesale and the retail level. At the same time it poses technical challenges resulting from the need to ensure a smooth operation of the European power system. Methodologies for assessing the adequacy need to be adapted in the presence of more RES-E [2]. Finally, investments are taking place into new technological solutions, helping to integrate RES-E as e.g. energy storage.

Power system models are the tool of choice for assessing options along the three policy dimensions (market design, RES-E integration, research and innovation). High quality wind power and PV time series for long time periods are needed in order to produce model results that translate into robust policy advice. Moreover, data should be publically available if impact assessments are to be transparent and reproducible. However, no such dataset currently exists for Europe. The EMHIRES dataset addresses this need and provides a publically available time series for the generation of intermittent RES-E derived from meteorological data.

EMHIRES applies an innovative methodology capturing local geographical information to generate meteorologically derived wind power time series at high temporal and spatial resolution. This allows for a better understanding of the wind resource at the precise location of wind farms. EMHIRES is able to capture the variability of wind energy, in particular peaks and ramps, in a much more accurate way than previous meteorologically derived time series. Using EMHIRES for power system analysis will increase the accuracy of generation adequacy assessments, renewable energy integration studies and market studies for flexibility technologies such as storage.

This report details the first part of EMHIRES, covering wind energy production. Further publications are planned on PV energy and temperature corrected power demand. The datasets can be reviewed and readapted to new situations in the power system (e.g. the commissioning of new installations) as well as to future RES-E deployment scenarios.

Chapter 1 explains the nature and cope of the work. The primary data sources used for creating EMHIRES are described in Chapter 2. Chapter 3 describes the methodology used for deriving wind power time series from meteorological data and information on wind power technology. In Chapter 4, the generated time series are compared with other data sources. Possible applications and possible future work is explained in Chapter 5.

1 Introduction

The electricity sector is currently experiencing a structural transition. The goal of the European Union for Renewable Energy Sources (RES-E) to provide for at least 27% of the total energy consumption by 2030 could translate into 50% of total electricity production from renewables (RES-E) [1]. The Energy Union strategy includes the aim of the European Union to become "the number one in renewables" continuing the significant growth of RES-E experienced during the last decade [1].

However, the growing share of electricity production from solar and wind resources constantly increases the stochastic nature of the power system. As a consequence, planning and scheduling tools for the power sector have been updated and the study of power systems with a high share of intermittent RES-E has become an established field in Power System Analysis.

The adequate modelling of high RES-E penetration systems crucially depends on the accurate representation of the spatial and temporal characterisation of these sources. RES-E data inherently bears the risk of being imperfect, inappropriate or incomplete which might lead to errors in power system studies which could be either overstating or downplaying the possible role of solar and wind energy in the future energy mix [3].

In the case of wind power assessment, currently, there seems to be a clear trend to use weather derived time series generated by reanalysis, or the output from meteorological models, and then, to convert those results into power output using approximations of standard power curves applied for entire market areas, such as the studies developed by Electricité du France – European Electricity System with 60% RES [4], ADEME – Vers un mix électrique 100% renouvelable en 2050 [5] and NREL – Renewable Electricity Futures Study [6]. Any RES-E dataset used for assessing the European power system should keep a compromise between the geographical coverage, spatial resolution accounting for European climate zones and the diversity of the wind features as well as time intervals and period long enough to capture the climate variability. Care needs to be taken with respect to technical data of wind turbines such as hub height and power curves of each turbine type at each wind farm. However, there currently exists no publicly available robust datasets meeting all these requirements [7].

The Knowledge Management Unit at the directorate for Energy, Transport and Climate, DG-Joint Research Centre (JRC) has developed the EMHIRES dataset (European Meteorological HIgh resolution RES time series) to fill this gap. This first report describes the first part of the work; leading to the development of EMHIRES Wind Power Generation database. This database is released as open-source according to the JRC Data Policy.

1.1 Scope of EMHIRES

EMHIRES provides RES-E generation time series for the EU-28, Norway, Switzerland and the non EU countries of the Western Balkans. The wind power time series are released at hourly granularity and at different aggregation levels: by country (onshore and offshore), power market bidding zone, and by the European Nomenclature of territorial units for statistics (NUTS) [8] defined by EUROSTAT; in particular, by NUTS 1 and NUTS 2 level.

The time series provided by bidding zones include special aggregations to reflect the power market reality where this deviates from political or territorial boundaries, such as in Ireland (Republic of Ireland and Northern Ireland forming one market zone), Norway, Sweden, Denmark and Italy (separated in 5, 4, 2 and 6 different zones, respectively where there is installed wind farms). In the case of Greece, the time series are released for the interconnected zone, i.e. the wind farms located on islands that are not connected with the mainland power system, are excluded.

The overall scope of EMHIRES is to allow users to assess the impact of meteorological and climate variability on the generation of wind power in Europe and not to mime the actual evolution of wind power production in the latest decades. For this reason, the hourly wind power generation time series are released for meteorological conditions of the years 1986-2015 (30 years) without considering any changes in the wind generation fleet. The installed wind farms fleet is then fixed as the one installed at the end of 2015. For this reason, data from EMHIRES should not be compared with actual power generation data other than referring to the reference year 2015.

In order to overcome the known limitations arising from the direct use of reanalysis data in wind power generation modelling, the meteorological data is derived from a highly detailed wind resource applying a novel geographical downscaling methodology that has been validated during this work.

1.2 Comparison of EMHIRES with other datasets

EMHIRES is a high quality (high temporal and geographical resolution) dataset of RES-E time-series derived from weather data and from information on the wind/solar power generation facilities installed across Europe.

Currently, there are three major publically available datasets for RES-E generation, all offering at least the spatial coverage of Europe.

- The 'Global Atlas for Renewables' managed by the International Renewable Energy Agency (IRENA) [9],
- The 'Global Wind Atlas' of the Danish Technological Institute (DTU) [10] and
- 'Renewable.ninja' developed jointly by the Swiss Federal Institute of Technology in Zurich (ETHZ) and the Imperial College of London [11].

A number of non-public datasets using similar methodology have been also created recently, such as e.g. the Pan European Climate Database (PECD) used by ENTSO-E for regional adequacy assessments (based on [12]). The information provided on this dataset does not allow for an in depth comparison with EMHIRES.

The Atlases from IRENA and DTU publish annual and monthly averages of wind and solar power production at any location in the world on a web based platform. Such datasets are typically used by long term energy system models with few inter-annual time slices. The atlases do not however contain time-series with a sub-annual resolution. Like EMHIRES, they have been derived combining weather data and information on renewable energy technologies. Renewable.ninja contains hourly time series at country level such as the EMHIRES dataset and thus addresses comparable applications. The approach to obtain the time series ([13] and [14]) is comparable to EMHIRES: it uses the same primary source for weather data but follows a simpler approach in the conversion to wind power output. The low resolution weather variable is corrected with a bias-correction factor determined at country level, missing the information of the physical local effects such as the speed up due to orographic or roughness effects and the increased variability as a function of the wind direction. Indeed these features are known not to be captured by using coarse resolution reanalysis or applying a power correction factor at country level; and not being able to aggregate at different aggregation levels (NUTS 1, NUTS 2 or bidding zone).

The strength of EMHIRES with respect to those three alternatives lays in the combination of the most recent advances in the fields of weather and wind power. EMHIRES uses a new approach based on the Wind Global Atlas to obtain high quality hourly weather data (wind speed) at the locations of wind farms. The dataset has been validated with the most recent high resolution wind resource products, released by the European Centre for Medium-Range Weather Forecast (ECMWF) [15]. As opposed to the other datasets, EMHIRES takes into account wind farm specific power curves for each location. In addition, EMHIRES is currently the only source of RES-E generation time series published at different regional scales, namely: Member State, ENTSO-E bidding zone, and NUTS 1 and NUTS 2 regions.

2 Data and tools

This section describes the data used to generate the EMHIRES wind power time series: i.e., the primary meteorological datasets and the wind farms dataset characteristics to convert wind speed into power.

2.1 Wind farms data

The wind farms database procured from the 'thewindpower.net' [16] has been used as the primary source to define the characteristics of each wind farm included in EMHIRES. The original database includes worldwide information for onshore and offshore wind farms, reporting 292 GW (20,635 wind farms) of onshore wind farms in operation and 23 GW (510 wind farms) under construction as for the end of 2015. For the same cutting date, as regards offshore wind farms, the database includes 10 GW (122 wind farms) in operation, 6 GW under construction (32 wind farms), 41 GW approved (125 wind farms) and 173 GW (471 wind farms) planned.

The original database contains a significant amount of gaps, inconsistencies and inaccuracies; therefore it has been reconstructed by gap filling and statistical homogenisation. To validate the improved database the aggregated installed capacities have been compared with data from (among others) different European Transmission System Operators (TSOs). A detailed description of the wind farms database improvements is given in paragraph 3.3.

2.2 Meteorological data

The primary source of meteorological data used in EMHIRES comes from the **NASA atmospheric reanalysis dataset** which was generated within the Modern Era Retrospective-Analysis for Research and Applications (MERRA) project [17]. The MERRA dataset has an hourly temporal resolution as opposed to other reanalysis datasets which are only published in intervals of several hours. It has shown a good correlation with wind measurements at relevant heights. Pearson's correlation coefficients are around 0.85 on an hourly basis and 0.94 on a monthly basis for measurements in terrain with low complexity [17].

MERRA has been chosen for developing EMHIRES because it is the only validated source at hourly frequency covering a period of 30 years over Europe, calibrated ex post with measurements. The MERRA reanalysis integrates a variety of observing systems with numerical models to produce a temporally and spatially consistent synthesis of observations. The ex-post calibration is one of the main aspects in which reanalyses differ from a meteorological model which solves equations describing the physical atmospheric processes using statistical approximations and weather observations just as input.

MERRA datasets are the output of the Goddard Earth Observing System Model v.5 (GEOS-5) and it's Atmospheric Data Assimilation System (ADAS), version 5.2.0. The data streams assimilated by the GEOS-5 DAS come from radiosondes, pilot balloon winds, wind profiles, radar winds, aircraft reports, dropsondes, spectroradiometer (MODIS water vapour winds), surface land observations, surface ship and buoy observations.

The variables selected for EMHIRES come from the "IAU 2d atmospheric single-level diagnostics" products, extracted from the 'on-the-fly' and daily data sub-setting product [18]. The native horizontal resolution is 0.66-degree longitude by 0.5-degree latitude (70 km x 60 km approximately in the area covered by EMHIRES: West -11^{o} North 73^{o} South 35^{o} and East 40^{o}) and it is available at 72 levels. Surface data, near surface meteorology, selected upper-air levels and vertically integrated fluxes and budgets are produced at one-hour intervals. The 30 year-period selected ranges from the 1st of January 1986 to the 31st of December 2015 from 00:30 to 23:30 Universal Time Coordinates (UTC) at hourly frequency. The variables extracted are:

- Eastward and Northward wind at 2m above displacement height (ms^{-1}) (U2m, V2m);
- Eastward and Northward wind at 10m above displacement height (ms^{-1}) (U10m, V10m);
- Eastward and Northward wind at 50m above displacement height (ms^{-1}) (U50m, V50m);

The **ECMWF high resolution wind products at 100m**, available from the European Centre for Medium-Range Weather Forecasts (ECMWF) is used for validating the high resolution time series generated in EMHIRES for the years 2012 to 2015. As the ECMWF dataset is only available for 4 years, it was not used as a primary source for generating the EMHIRES time series [19]. It is not an open-source dataset and has been obtained by JRC under its current cooperation agreement with ECMWF.

The new dataset represents a valuable improvement with respect to coarse reanalysis data and to the direct extrapolation of ECMWF 10-m wind, which was shown to produce a considerable degradation of energy power production with respect to observed values [19]. The new variable of ECMWF meets the need of calculating the wind speed at turbine height level, and is the result of the vertical linear interpolation from the two nearest ECMWF model levels, which are, respectively at approximately 70 and 110 m. In order to obtain hourly data, horizontal wind fields are taken from ECMWF analyses at 00:00 and 12:00 UTC, and, for the remaining times, from the short-term forecasts in the range +1 - +11 hours. At such a very short range, the forecasts are nearly indistinguishable from the analyses, so that they can be used as realistic surrogates at the times when the latter are missing (also, we do not consider the analyses at 06:00 and 18:00 UTC but the forecast at +6 h). Data cover a wide region extending from 30°N to 75° N and from 25° W to 45°E, considering both onshore and offshore grid points almost all over Europe, including Iceland.

2.3 Actual wind power generation time series and statistics

The calculated wind power time series in EMHIRES are validated against the actual wind power generation outputs provided by the Transmission System Operators (TSOs) for the year 2015 at country level and by bidding zone[1]. The non EU Members from the Western Balkans are also included although the currently installed capacity is negligible. The main source for TSOs time series is the Transparency Platform provided by the European Network of Transmission System Operators for Electricity (ENTSO-E) [20] in agreement with Regulation 543/2013 [21]. In case data are not available on the ENTSO-E transparency platform (e.g. Croatia or Italian bidding zones) or contains significant amount of missing values (e.g. United Kingdom, Republic of Ireland, Cyprus), data from the corresponding National Transmission System Operator was preferred as a source. Regardless this, in a few cases it has been impossible to obtain time series (e.g. Bulgaria, Luxemburg, Slovenia and Slovakia).

Table 2 shows the availability and source of the time series used for the validation and the basic descriptive statistics of the observed time series. To crosscheck the level of accuracy of the ENTSO-E and national hourly time series, the sum over all hours in 2015 is compared with the annual generation reported by the same source in a different

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[1] According to Regulation 543/2013, bidding zones are the largest geographical areas within which market participants are able to exchange energy without capacity allocation. Bidding zones in Europe are usually defined by national borders; however, some are larger than national borders (e.g. Austria and Germany) while other zones extend only over a part of a country due to structural characteristics of the national transmission system (e.g. Italy, Norway or Sweden) or because of the presence of different synchronous systems (e.g. Denmark).

section of its web data repository. It is observed there are mismatches for most of the countries between the total annual production reported and the sum of the hourly reported values.

The ENTSO-E time-series include hours that are not registered while the total annual generation could have been metered and reported separately e.g. for support scheme payments. For example 68% of hourly values of the ENTSO-E time series for Bulgaria are missing on the transparency platform yet an annual value is published by the same organisation.

ENTSO-E publishes detailed generation figures for units with installed capacity equal to or above 100 MW, as well as aggregated generation outputs per market time units and production types. According to Regulation 543/2013, the information shall be provided for all bidding zones only in Member States with more than 1 % feed-in of wind or solar power generation per year or for bidding zones with more than 5 % feed-in of wind or solar power generation per year.

The EMHIRES wind power time series are normalised to the ENTSO-E annual production statistics reported (values in bold in Table 2). This analysis does not compare these figures to national statistics or data reported for determining the subsidies received by operators of wind farms. The reasons that national borders do not always coincide with market zones (e.g. Denmark, United Kingdom), renewable energy produced might be outside of the interconnected system (Greece) or generation by auto-producers might not be included in the statistics of the TSO.

The EMHIRES dataset also includes time series by NUTS 1 and NUTS 2 (see the tables in the annex) region. For the validation at NUTS 1 and NUTS 2 level a search has been done for regional statistics. However, for most of the countries, neither time series nor monthly or annual statistics are yet available for 2015. Some EU Member States (e.g. the UK) will publish annual statistics on a regional level at the time of release of this report. In the case of Spain [22], there are monthly statistics of wind generation by region, and in the case of France [23] and Finland, the statistics available show the total annual production by regions (Figure 1 and Table 1). The territorial reform of France, which became effective in 2016, led to new NUTS 1 and NUTS 2 regions as shown in the table below.

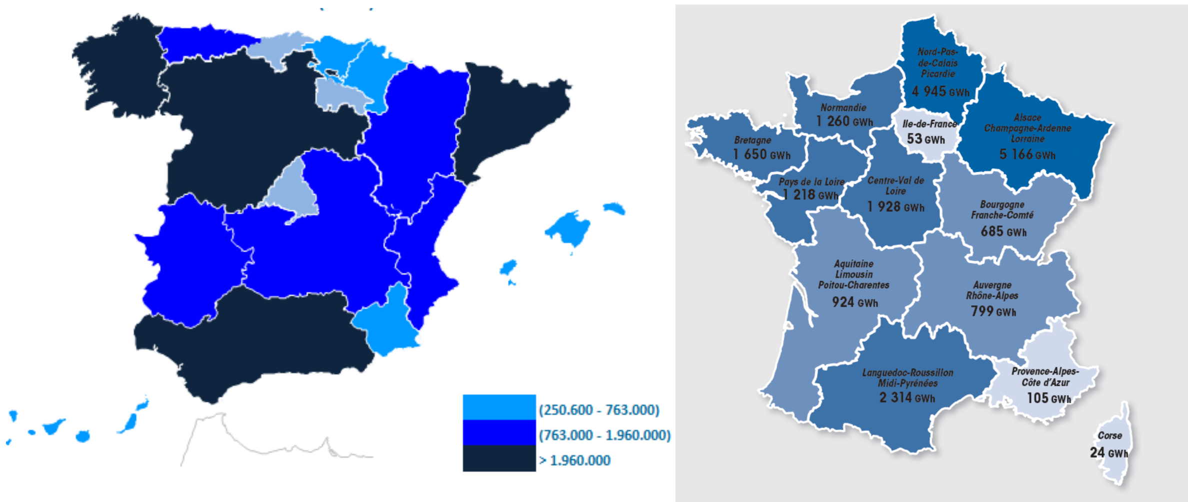

Figure 1 Example of monthly and annual total production by regions for Spain and for France, respectively.

Table 1 - Translation of existing NUTS-2 codes to the new French territorial regions

Regions defined in EMHIRES	NUTS 2 codes
Auvergne-Rhône-Alpes	FR72,FR71
Bourgogne-Franche-Comté / Bourgogne Franche-Comte	FR26,FR43
Bretagne	FR52
Centre-Val de Loire	FR51, FR24
Corse	FR83
Grand-Est / Alsace Champagne-Ardenne Lorraine	FR41, FR42,FR21
Hauts-de-France / Nord-Pas-De-Calais- Picardie	FR30, FR22
Ile-de-France	FR10
Normandie	FR23,FR25
Nouvelle-Aquitaine / Aquitania, Limousin, Poitou-Charentes	FR61, FR63, FR53
Occitanie / Languedoc-Roussillon Midi Pyrenees	FR81, FR62
Pays de la Loire	FR51
Provence-Alpes-Côte d'Azur	FR82

Table 2 availability and source of the time series used for the validation and the basic descriptive statistics for the ENTSOE wind power time series for 2015

Country	Bidding zone	Source	25p	50p	Mean	75p	Max	%NA	Sum h (GWh)	Annual (GWh)
Austria (AT)		ENTSO-E	132	377	561	862	2176	0	4912	**3989**
Belgium(BE)		ENTSO-E	73	190	280	419	1053	1	2429	**5380**
Bulgaria (BG)		ENTSO-E	34	101	149	236	570	68	419	**1436**
Switzerland (CH)		ENTSO-E	2	4	5	8	31	1	52	**132**
Cyprus (CY)		DSM	5	15	20	30	111	10	79	**231**
Czech Republic (CZ)		ENTSO-E	26	52	68	94	280	0	596	**563**
Germany (DE)		ENTSO-E	2894	5690	7859	11102	31162	1	68284	**75680**
Denmark (DK)	DK1 DK2	ENTSO-E	325	788	1009	1599	3756	0	8837	**14086**
Estonia (EE)		ENTSO-E	26	55	72	107	234	1	624	**696**
Spain (ES)		ENTSO-E	2887	4884	5477	7469	17436	0	47892	**48107**
Finland (FI)		ENTSO-E	100	202	236	326	818	0	2059	**2329**
France (FR)		ENTSO-E	1103	1736	2238	3012	7450	0	19592	**21067**
Greece (GR)		ENTSO-E	147	323	405	625	1412	0	3540	**3744**
Croatia (HR)		HOPS	21	64	90	151	324	0	788	**788**
Hungary (HU)		ENTSO-E	18	56	81	121	304	10	642	**670**
Ireland (IE)	Ireland (SEM)	EIRGRID	266	674	759	1211	2024	0	2027	**6536**
Italy (IT)	NORD, CNOR, SUD, CSUD, SICI, SARD	TERNA	NA	NA	NA	NA	NA	0	NA	**14707**
Lithuania (LT)		ENTSO-E	19	57	81	127	327	3	697	**805**
Luxemburg (LU)		NA	NA	NA	NA	NA	NA	100	NA	**95**
Latvia (LV)		ENTSO-E	3	8	12	19	44	0	105	**146**
Netherlands (NL)		ENTSO-E	353	765	972	1456	3114	44	5674	**7134**
Norway (NO)	NO1 – NO5	ENTSO-E	NA	NA	NA	NA	NA	0	NA	**2515**
Poland (PL)		ENTSO-E	410	918	1210	1783	4223	0	10570	**10365**
Portugal (PT)		ENTSO-E	495	1026	1294	1923	4192	0	11335	**11336**
Romania (RO)		ENTSO-E	208	543	754	1161	2687	8	6079	**6993**
Sweden (SE)	SE1 - SE4	ENTSO-E	1023	1751	1894	2651	4958	1	16410	**16618**
Slovenia (SI)		NA	NA	NA	NA	NA	NA	100	NA	**NA**
Slovakia (SK)		NA	NA	NA	NA	NA	NA	100	NA	**6**
United Kingdom (UK)	GB	ELEXON	71.5	1261	2407	2668	3999	0	8515	**23963**

3 Description of methodology

The general approach to convert wind resources into power generation consists in converting wind speed data from weather models or observations using power curves. The power curves, which are turbine-dependant, provide the value of electrical power output as a function of wind speeds at the hub height. The approach followed to develop EMHIRES converts the wind resources into power generation combining a high detailed wind farm database with a high spatial and temporal resolution wind speed dataset. The methodology used for EMHIRES is summarised in Figure 2.

This section describes in detail the methodology applied and the IT infrastructure and the software used while next section 4 summarizes the results obtained and their validation.

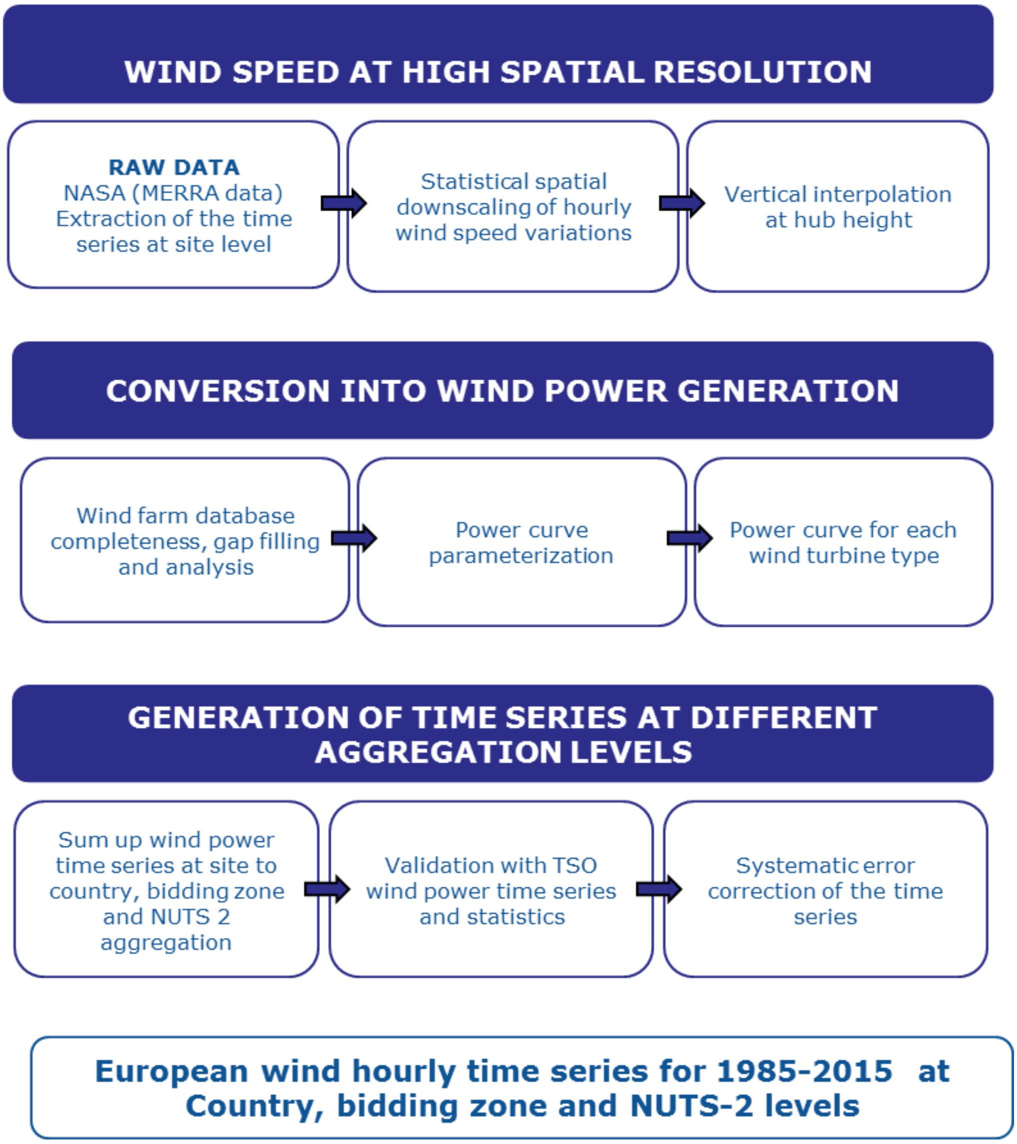

Figure 2 Summary of the steps followed to develop EMHIRES dataset

3.1 State of the art

One of the most important aspects when generating wind power from the wind resource is how to deal with the uncertainties. A cascade of uncertainties emerges from different parts of the methodology and tools applied for transforming a meteorological variable into power generated, as e.g. described by [24] (Figure 3).

Among all RES-E, wind power forecasts have the highest uncertainties mainly due to the temporal and spatial variability and the little predictability of the wind resource. If the wind speed is selected from a meteorological model, this could add a bias in the wind fields (determined at 10 m height or at other model levels) because the physical parameterisations of the meteorological model do not perfectly simulate the dynamics of the lower layer of the atmosphere. Moreover, the wind fields, obtained at 10 m height or at other model levels, need to be corrected to the hub height and this interpolation method also contributes to the uncertainty [25].

The wind speed is then converted into wind power generation through a power curve. The selection of the power curve is also critical since each type of turbine has a different power curve. The area of the wind farm, the number and location of the turbines composition, its geographical position and the wake effect originating from the fluid dynamic interactions inside wind farms play an important role in the accuracy of forecasting wind power generation (see for example [26]).

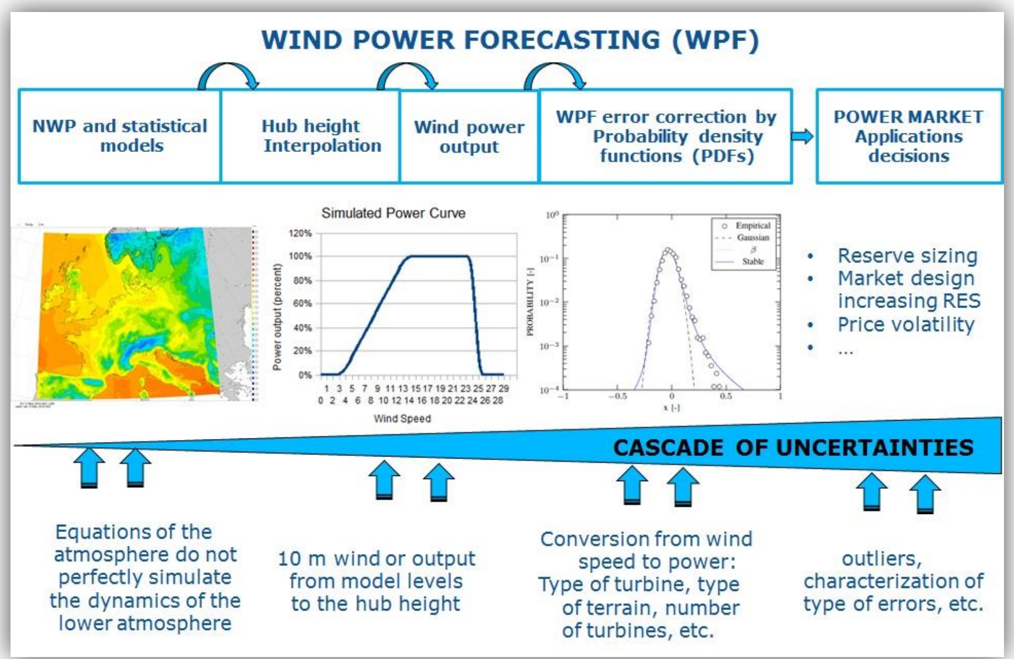

Figure 3 Sources of errors in the wind power forecast contributing to the cascade of uncertainties

To deal with and reduce the uncertainties, the studies identified in the literature aim at either:

- Developing more accurate numerical and statistical wind power forecasting techniques, or,
- Studying the wind power forecasting error (WPFE) as a single probability density function, describing the error variability as a range from the lowest to the highest value of the distribution in the historical records.

A detailed review about the methods and advances in forecasting wind power generation can be found in [27]. Studies focused on reducing the WPFE apply techniques that identify probability distributions of random variables and calculate their distribution parameters based upon historical trends.

3.2 Wind speed at high spatial resolution

The following subsections describe the methodology used in EMHIRES to obtain high spatial and temporal resolution wind speed data at the hub height of each wind farm. As a first step, the wind components are extracted from the NASA-MERRA reanalysis and pre-processed; then, a new statistical spatial downscaling technique is applied to obtain the wind speed time series, and finally a power law profile is used to vertically interpolate the wind speed at hub height.

3.2.1 Extraction of the time series at site level

Hourly eastward and northward wind components at three different heights 2, 10 and 50 m have been obtained from MERRA, in NetCDF format, on a grid of 60 km x 70 km resolution approximately for the study period ranging from 1986 to 2015. These gridded hourly values are interpolated at each wind farm location where the wind speed and direction is calculated on the basis of equations. (1) – (3)

$$DperR\ (180/\ \pi)\ = 57.29578 \tag{1}$$

$$Dir = atan2\ (-u, -v) * Dper = 270 - (atan2(v, u) * DperR) \tag{2}$$

$$WS = sqrt\ (u^2 + v^2) \tag{3}$$

Where *DperR* is the argument arctangent functions to convert angles into radians needed to obtain the geographic wind speed. Dir Is the direction with respect to true north, (0=north, 90=east, 180=south, 270=west) and WS is the horizontal wind speed.

3.2.2 Statistical spatial downscaling of hourly wind speed variations

Although the data used are taken from a reanalysis and consequently should have lower errors compared to forecasts, there are still uncertainties partly due to the limited spatial resolution. The spatial resolution selected (60 km x 70 km) is too coarse to capture local effects. Figure 4 shows why the spatial resolution of the wind resource data is relevant, taking as an example a coastal area. In this case, it is very evident as high wind spots are not captured using low resolution data. Using coarse resolution meteorological data for power system analysis can lead to significant errors. A deviation of 10% of the total annual production would result in the case of Spain [3] Therefore, in EMHIRES a statistical downscaling technique is applied to capture the effect of fine-scale forcing, in particular in areas characterised by fine spatial variability of features such as rugged topography, very diverse land surface conditions or sea-land interactions.

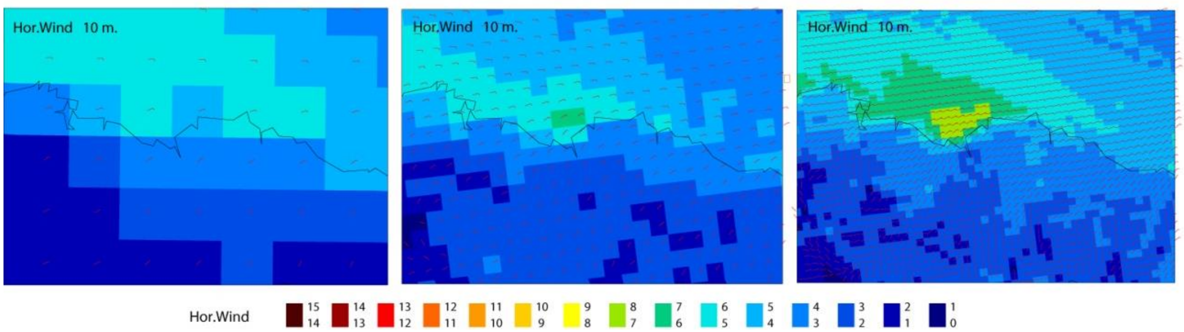

Figure 4 Typical wind speed file from a meteorological model or a reanalysis including three spatial resolutions (15, 5, 2 km).

The downscaling technique is applied to capture local effects due to the orography and the roughness of the terrain. It is not applied to the offshore wind farms for which the power generation is calculated from MERRA primary data.

The technique employed is a robust and established technique based on a probabilistic approach and aimed at predicting the changes in the probability density function (pdf) of local scale wind speed conditioned on large-scale hourly wind speed predictors [28]; [29]. The analytical expression summarizing the methodology was developed in [30] and applied to downscale daily wind speed time series form a meso-scale meteorological model to the wind farm level.

EMHIRES is based upon the same algorithms as used by [30] but the large scale time series are available at hourly-based frequency (namely, the HIRES dataset) while the microscale hourly wind speed distribution is provided by the Global Wind Atlas (GWA) developed by the Danish Technical University.

For each wind farm location, the Weibull distribution function best describing the HIRES hourly data series is computed and parameters A_{meso} and k_{meso} determined for both the 10m and 50m heights. In the same locations and for the same heights, A_{micro} and k_{micro} given by Global Wind Atlas are also collected. For both probability distribution functions (Figure 5), the related cumulative distribution functions F_{micro} and F_{meso} are computed by the Weibull distribution properties as

$$F_x(X) = 1 - \mathrm{e}^{-\left(\frac{x}{A}\right)^K} \tag{4}$$

Each value of x_{meso} arising from the HIRES hourly time series (4) it is then associated to the value of x_{micro} leading to equal values of F_{meso} and F_{micro}, as described in equations (5) and (6)

$$F_{micro}(Xmicro) = F_{meso}(X) \tag{5}$$

$$1 - \mathrm{e}^{-\left(\frac{x_{micro}}{A_{micro}}\right)^{k_{micro}}} = 1 - \mathrm{e}^{-\left(\frac{x_{meso}}{A_{meso}}\right)^{k_{meso}}} \tag{6}$$

Leading to the following direct relation between x_{micro} and x_{meso} that has been practically implemented in the downscaling software

$$x_{micro} = A_{micro}\left(\frac{x_{meso}}{A_{meso}}\right)^{\frac{k_{meso}}{k_{micro}}} \tag{7}$$

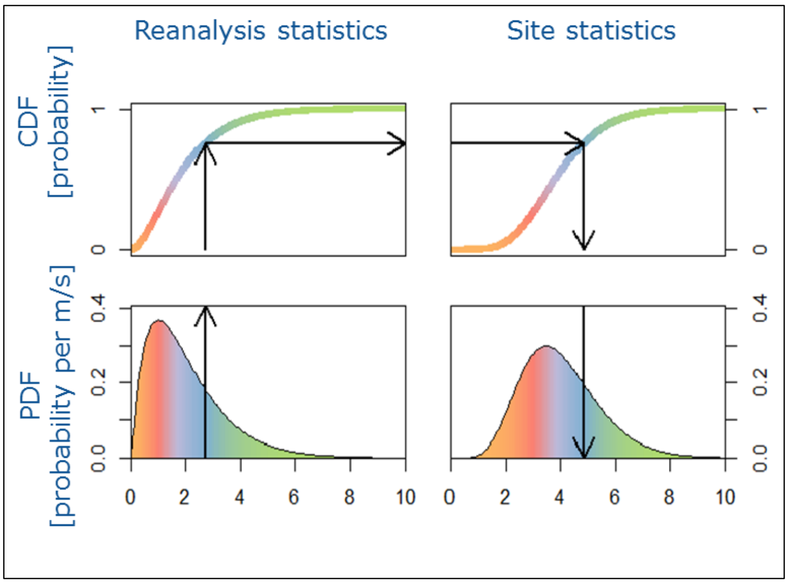

Figure 5 Shows in a graphical form the downscaling procedure applied.

To calculate the wind power generation time series, the HIRES wind speed time series are then vertically interpolated to the hub height of each wind farm using a power law profile.

$$WS_2 = WS_1 \frac{ln\left(\frac{h_2}{z_0}\right)}{ln\left(\frac{h_1}{z_0}\right)} \rightarrow \alpha = \frac{log\left(\frac{WS_1}{WS_2}\right)}{\log\left(\frac{h_1}{h_2}\right)} \tag{6}$$

The value of α is calculated using the MERRA-derived wind speed time series at 10 and 50 m height. Once α is identified, the same profile is used to estimate the wind speed at the given hub height of each wind farm (WS_{HH}).

$$WS_{HH} = WS_1 \left(\frac{HH}{h_1}\right)^{\alpha} \tag{7}$$

However, although a finer spatial resolution gives more accurate results, in some cases it adds an extra factor to the uncertainties' cascade, that is, the progressive accumulation of all sources of uncertainty. Therefore, to assess the degree of improvement of the downscaling technique additional wind speed datasets are used to analyse the variability and correlation of wind speeds at different spatial resolutions. Three different datasets have been selected for the comparison, namely:

- **MERRA100**: 100 m wind speed time series vertically interpolated form 10 and 50 m wind speed MERRA reanalysis (70 km x 70 km spatial resolution)
- **ECMWF100**: 100 m wind speed (12 x 12 km spatial resolution) extracted from the ECMWF available for a period four-years period (2012-2015)
- **HIRES100**: 100 m wind speed at 100 m downscaled to wind farm level. This is the dataset developed in EMHIRES, applying the downscaling technique to the MERRA reanalysis.

3.3 Conversion into wind power generation

The wind speed at hub height is converted into power using the reconstructed wind farm database from 'thewindpower.net'.

In order to define a robust wind farm database the original data acquired from the commercial data provider underwent a data quality and data gap filling procedure. Moreover, a wind power curve was associated to each wind farm. This procedure has involved wind farms declared in production phase (status = production) and commissioned before end 2015 (commissioning year <2016 or absent) and it is described in next two paragraphs (Figure 6).

After the reconstruction, the database contains 16171 wind farms located in European countries, 85 of which are offshore. In addition, to evaluate the quality of the database it has been compared the total installed capacity with ENTSOE statistical factsheet [31], studied the hub height distribution by country and by manufacturer versus commissioning year and turbine type and the distribution of the manufacturers by country. These add up to 95% of the installed capacity reported in the ENTSO-E statistical factsheet, while the original database matched 89% (Table 3).

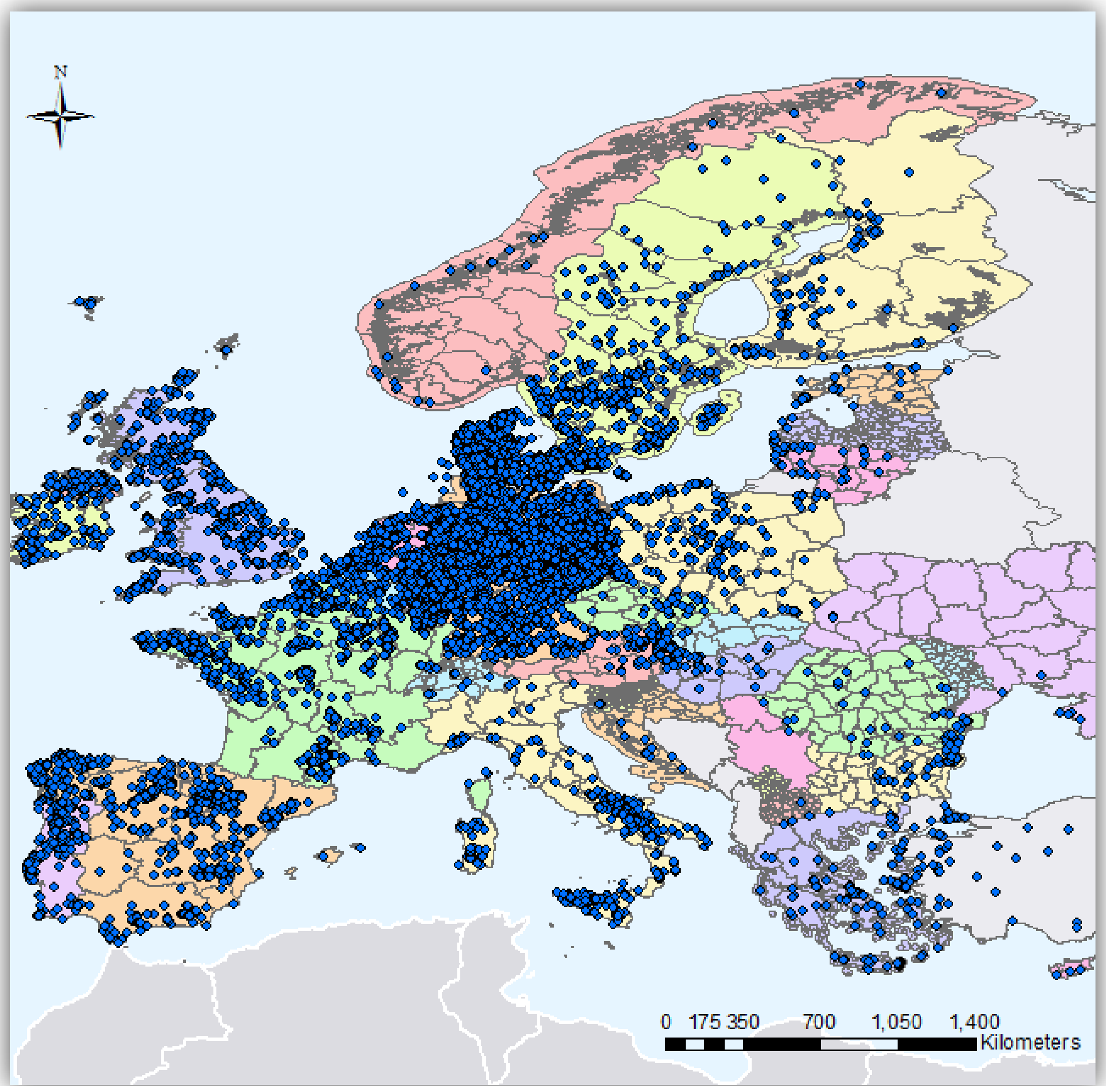

Figure 6 Wind farms locations across Europe as reported in the Wind Power database

Table 3 Comparison of the total installed power at the end of 2015 according to the Wind Farm Database (WFDB) and the ENTSO-E statistical factsheet before and after the geographical location gap filling.

Country	ENTSOE (MW)	WDFB (original) (MW)	WFDB (gaps filled)	Match WFDB (original) with ENTSOE (%)	Match WFDB (gaps filledr) with ENTSO-E (%)
Austria	1981	2084	2099	105.2	106.0
Belgium	2172	1861	1861	85.7	85.7
Bulgaria	701	586	637	83.7	90.9
Croatia	384	355	355	92.6	92.6
Cyprus	155	145	145	94.1	94.1
Czech	277	306	323	110.7	116.8
Denmark	5082	4645	5134	91.4	101.0
Estonia	301	290	302	96.5	100.5

Country	ENTSOE (MW)	WDFB (original) (MW)	WFDB (gaps filled)	Match WFDB (original) with ENTSOE (%)	Match WFDB (gaps filledr) with ENTSO-E (%)
Finland	1082	754	769	69.7	71.1
France	10312	9464	9585	91.8	93.0
Germany	43429	36044	38261	83.0	88.1
Greece	1775	1396	1869	78.7	105.3
Hungary	328	486	512	148.3	156.3
Ireland	2400	2076	2300	86.5	95.8
Italy	8750	8805	9469	100.6	108.2
Latvia	70	52	52	75.0	75.0
Lithuania	290	195	250	67.4	86.3
Luxembourg	600	560	58	93.8	97.2
Netherlands	3641	3108	3153	85.4	86.6
Norway	860	835	892	97.2	103.7
Poland	5186	3243	3356	62.5	64.7
Portugal	4826	4847	4931	100.4	102.2
Romania	2923	2552	2897	87.3	99.1
Slovakia	3	3	3	104.7	104.7
Slovenia	3	5	5	183.3	183.3
Spain	23003	22260	23237	96.8	101.0
Sweden	3029	3242	4173	107.1	137.8
Switzerland	60	60	60	100.0	100.0
UK	13563	12801	13412	94.4	98.9
Turkey	NA	3424	3949	NA	NA
Ukraine	NA	393	578	NA	NA
TOTAL	**131586**	**122568**	**130111**	**89.7**	**95.2**

3.3.1 Wind farm database completeness, gap filling and analysis

Missing values in the database include fields such as: the installed capacity of each wind farm, the number of turbines within a wind farm, turbine type, manufacturer, hub height, swept area, minimum power output, maximum power output and nominal power output, the geographical location including onshore or offshore siting, the distance to the shore, the commissioning year or the operational status.

Gap filling and the statistical approximations have been calculated based on a number of criteria described below.

Installed power of each wind farm

Farms with no figure provided for the installed power (0.14% of the entries in the database) have been excluded from further analysis since there is no indication to fill the missing records.

Geographical location

For the wind farms with no indication of longitude and latitude but where the fields "city" and "area" were available; an approximate location has been found through Google maps (Table 3). Wind farms with missing longitude and latitude, city and area (6.5% of the total capacity) have been excluded from the list of farms used in the analysis. After filling the gaps the excluded installed power has been reduced to 3.5% of the total since the 3% of these records do not include any type of information (latitude-longitude, city or area).

Hub height of each wind farm

In the case of wind farms missing the "hub height" field, two options have been applied: If the 'turbine' field for a wind farm is filled in, the hub height is assigned equal to the average value of hub heights of all win farms of having the same turbine type, if available. If the 'turbine' field is not available for a wind farm, the hub height is assumed to be equal to the average of hub heights of the corresponding country (Figure 7). After gap filling, all records include a hub height: 39% of the records the original entry and 61% and estimate as described above. The Vestas V90 was found to be the most common turbine type in the database. There is also strong correlation between the hub height of the turbines and the year of the construction.

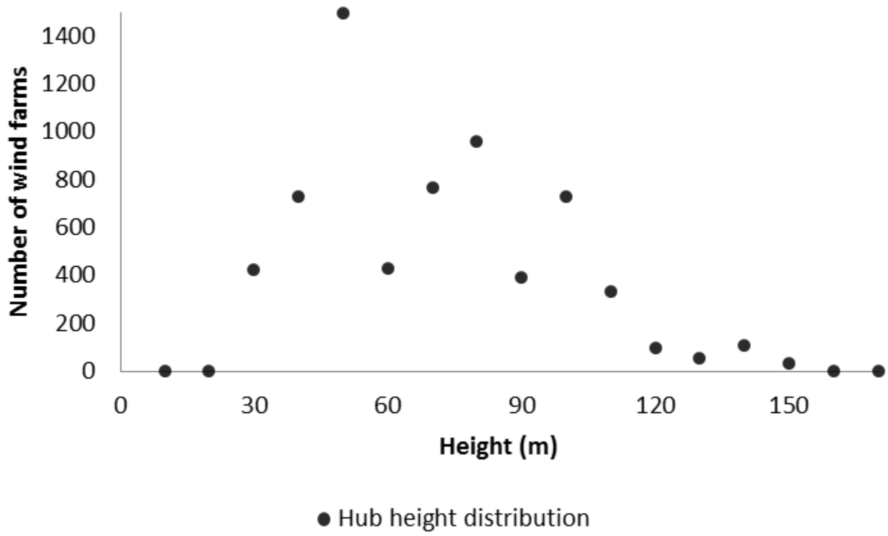

Figure 7 Hub height distribution of the original wind farm database for all countries selected

Country, bidding zone, NUTS 1 and NUTS 2 information

The original database did not contain information NUTS region in which wind farms are located. For this reason, the wind farm database has been spatially-joint with the European administrative units at NUTS-2 level using the ArcGIS v10.1 software. Using a shape- file [32] the administrative units have been spatially joined with the geographical coordinates (WGS84 georeferenced) of the wind farm database. It was possible to join 96.5% of the total records (16,736 wind farms). The remaining 3.5% are not included since no geographical information was available.

3.3.2 Power curve parameterisation

One power curve is assigned to each wind farm considering the characteristics of the wind farm: design of the turbine and manufacturer, and swept area of the turbines, installed power and minimum, nominal and maximum wind power.

The power curves are built using as primary data the turbine database from The Wind Power (wwwTheWindPower.dk) merged with an internal database including information of power curves that provides 1061 different power curves from 160 different manufacturers.

As described in the previous paragraph, after data check the database contains 16171 records to be assigned a power curve Records missing the direct indication of the turbine type are the 28% over the total. A power curve was associated to these records, based on the following criteria:

If at least partial information about the corresponding power curve was available (17% of the missing values), such as the minimum, nominal, maximum wind speeds and the power; an interpolation was calculated based on the fundamental equations of wind power. That is, the power output of the wind turbine depends on the amount of air (volume); the speed of the air (velocity) and the mass of air (density) flowing through the area of interest (flux). Based on the relation between kinetic energy, mass and speed,

$$KE = \frac{1}{2} * m * v^2 \tag{9}$$

The power of the wind turbine is the kinetic energy per unit of time:

$$P = \frac{1}{2} * \dot{m} * v^2 \tag{10}$$

$$\dot{m} = dm/dt = \rho * A * v \tag{11}$$

$$P_w = Cp * \frac{1}{2} * \rho * A * v^3 \tag{12}$$

Where $\dot{m} = dm/dt$ (mass flow), the equation based on fluid mechanics (11) gives the mass flux rate (density * volume flow). Then, the power P is a function of the cube of the velocity; it is thus proportional to the air density and to the area swept by the rotor. The power coefficient C_p, describes the fraction of the wind resource that is captured by the turbine.

$$C_p = \frac{P_t}{P_w} \tag{13}$$

The Betz limit [33] sets a maximum of $Cp = 59\%$ which is the best a conventional wind turbine can do in converting wind energy into electrical energy. In case that no data is available on the real power extracted by the turbine (given by each manufacturer for each turbine type, a correction factor (C_f) is interpolated between the minimum and the nominal thresholds by dividing the total wind power contained in the wind resource for each turbine (i.e. the theoretical power (P_t)) by the averaged power curve calculated for each manufacturer[2].

On the contrary, if there is no additional information and the 'turbine type' record is absent (11% of the missing cases), a statistical approximation is applied to assume a most probable power curve. Vestas is the largest manufacturer equipping 3,385 wind farms followed by Enercon with 2,432 wind farms, Neg-Micon with 1,046 wind farms and Gamesa with 805. Therefore, for missing values, the power curve for the Vestas V90 turbine (the most common in the database and for all countries) with 3MW of maximum power is assumed.

3.4 Generation of the time series at different aggregation levels

The wind power generation time series are calculated at each wind farm using the 30-year HIRES wind speed hourly time series and the reconstructed wind farm database.

The wind speeds of 30 years are converted into power using a power curve for each wind farm in the database that was operational in 2015. The wind power time series corresponding to 2015 are compared with actual generation time series provided by

[2] http://www.wind-works.org/cms/index.php?id=85&tx_ttnews[tt_news]=3935&cHash=39424df20f9c961ee7cd158a85cabe36

TSOs in order to evaluate the systematic bias and normalise the time series without modifying the variability, as described in next section 4.

The wind power generation time series are summed up at different aggregation levels. EMHIRES includes time series at country level and by bidding zone for the EU-28 and its neighbouring countries (Switzerland, Norway and Balkan regions, where there is any wind installed capacity). There are also special aggregations; for Ireland including the Republic of Ireland. For Greece the time series are released as continental Greece.

For the countries with high installed offshore capacity, the time series are in principle released as onshore and offshore wind power generation time series, separately. Nevertheless, the wind farm database contains 85 offshore wind farms in 15 countries: Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Lithuania, the Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom. No separate time series are provided for those countries that currently only have 1 or 2 offshore wind farms. Offshore wind power generation time series are released for the following regions.

- **Belgium** with 3 offshore wind farms registered in the database: NorthWind, BelWind and Thornton bank.
- **Denmark** with16 offshore wind farms registered in the database: Vindeby-Lolland, Tuno Knob, Horns Rev 1 and Horns Rev 2, Rønland, Frederikshavn, Nysted, Samso, Sprogo, Rodsand II, Avedøre Holme, Anholt.
- **Germany** with13 wind farms registered in the database: Emden, Breitling, Hooksiel, Alpha Ventus, EnBW Baltic, Bard Offshore, Riffgat, Dan Tysk, Meerwind Ost, Meerwind Süd and Butendiek.
- **The Netherlands** with 5 aggregated wind farms registered in the database: Irene Vorrink I, Irene Vorrink II, Lely, Egmond aan Zee and Prinses Amalia.
- **The United Kingdom** has the largest amount of installed offshore wind capacity in Europe (5 GW at the end of 2015). There are 28 wind farms registered in the database: Blyth, North Hoyle, Scroby Sands, Kentish Flats, Barrow, Beatrice, Burbo Bank, Lynn and Inner Dowsing, Rhyl Flats, Gunfleet Sands 1, 2 and 3, Robin Rigg, Thanet, Wave Hub, Ormonde, Walney, Greater Gabbard 1 and 2, Sheringham Shoal, Demonstration, London Array, Teesside, Lincs, Fife Energy Park, West of Duddon Sands, Gwynt y Mor, Westermost Rough, Humber Gateway.

In addition to time series at country and bidding zone levels; the dataset includes time series at NUTS 1 and NUTS 2 level except for the smallest countries and for countries with very small installed capacity (Estonia, Latvia, Lithuania, Czech Republic, Slovakia, Luxemburg and Cyprus). The country codes are summarized in the annex.

3.5 Software used

Different tools have been used for developing EMHIRES. The wind farm database (consisting of 103 variables, in a total of 16,171 records) and wind power generation time series published by TSOs are provided in the (xlsx) file format and can be easily manipulates using Microsoft Excel.

The two meteorological datasets (NASA-MERRA and ECMWF) and the input files of the Global Wind Atlas can be considered as 'big-data'. They contain more than 10 variables, for 30 years at hourly time intervals and at different heights. In addition, the grids are at 60 km x70 km resolution and in the case of the Global Wind Atlas at 250m x 250m. Those files are provided in the NetCDF format (Network Data Form) (Figure 8). They are processed using shell scripts, awk FORTRAN90, and the Climate Data Operators (CDO) on computers running the GNU/Linux operating system.

The code to develop EMHIRES is also written in a Linux environment using mainly shell script and the R-software (v3.1.2) for the statistical analysis. Data visualization and the dissemination of results are done using ArcGIS v10.1, NC-view and the Panoply software.

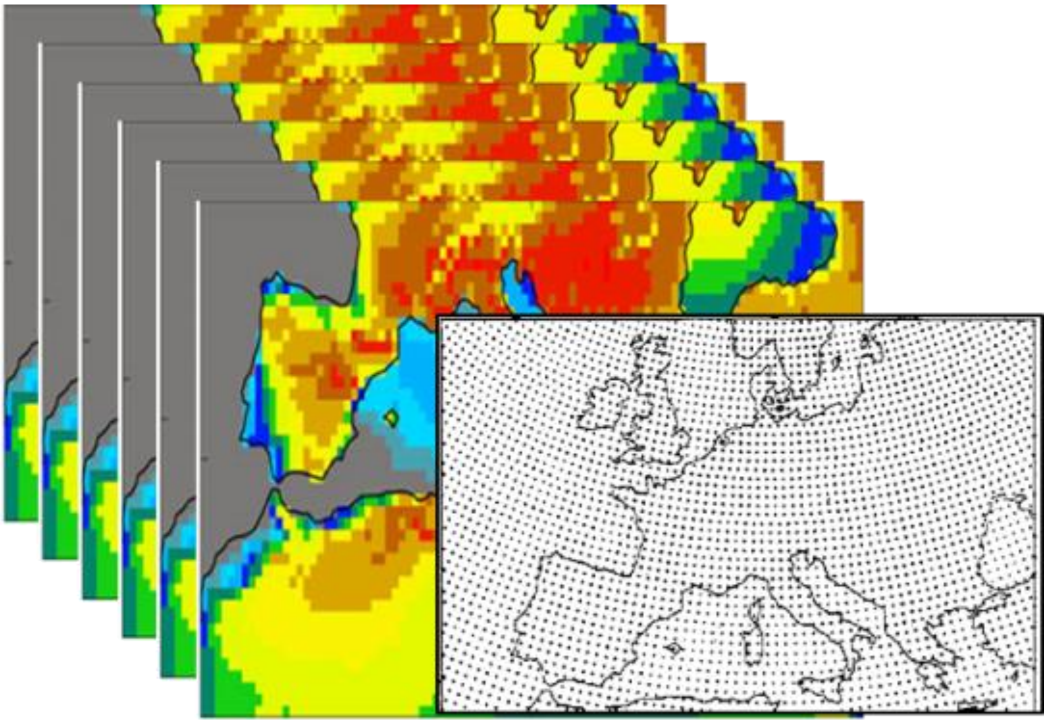

Figure 8 Example of NetCDF meteorological files with four dimensions: latitude and longitude, height and time.

The IT- infrastructure for EMHIRES consists of a single Linux machine (Virtual Machine) on which basic operations and tests calculations are performed. The final calculations are performed on the High Performance Computing clusters available at the JRC site in Petten, the Netherlands.

The Virtual Machine is running under VMware, with four CPUs, each equivalent to an Intel Xeon E7-4860 and 2.27 GHz core with 8 GB of RAM and 120 GB of disk space.

The HPC was commissioned in March 2013. It consists of 656 compute cores and 5.116 TB of memory on the compute nodes, spanning 2 cracks. The EMHIRES dataset has been developed on two of its computer nodes, characterised by 2 Intel Xeon E5-2630v3, 2.4GHz, 8-core processors (in total 16 cores per compute node and 64GB of DDR4 memory). Since the development of EMHIRES involves a high amount of data handling, disk storage of 50 TB plus 50 TB for archiving has been used.

4 Results and discussions

In this section the wind power series, aggregated at country, by bidding zone and by NUTS 1 and NUTS 2 level, obtained with the EMHIRES approach are presented and discussed, with a special attention to the impact of wind speed spatial resolution on power generation at different aggregation levels. In case of countries with significant offshore wind farms have been validated as the total (offshore + onshore) and offshore wind power generation time series have been validated, separately.

The first part of this section focuses on the validation of the wind power time series derived from different spatial resolutions of wind speed. MERRA and HIRES wind speed time series are compared with the ECMWF dataset at 100 m height for 2012-2015. The purpose is to assess the consistency of the downscaling applied to MERRA dataset (HIRES).

The second part presents the assessment of the wind power dataset improvement (EMHIRES) using the higher spatial resolution wind resource (the HIRES wind speed time series). Different statistical performances show the significance, the type of errors and the skill of the synthetic time series at different regional levels with respect to the actual wind power generation for 2015.

The last part consists of a description of the EMHIRES data format, and the platform where users can find the files and the terms of use of EMHIRES.

4.1 Comparison of wind speed from different datasets

This section presents the comparison of hourly wind speed time series at 100 m for 2012-2015 between MERRA, HIRES and ECMWF datasets.

The internal consistency of a dataset measures the reliability between similar results characterised of a set of test scores that relates to the amount of random error from the measurement process that might be embedded in the scores. The internal consistency of MERRA, HIRES and ECMWF datasets is assessed by the Pearson's correlation coefficient (R). The level of the correlation shows the linear relationships between them.

To gauge the statistical significance of the datasets, the Student's t-test is applied to the statistical indicators. The t-test is based on the formulation of the null hypothesis which states that there is no effective difference between the observed sample mean and the hypothesized or stated dataset mean—i.e., that any measured difference is due only to chance. As the sample size increases (and thus, the degrees of freedom - the number of independent observations in the sample minus one) the t-distribution approaches "the bell shape" of the standard normal distribution. If the observed t-statistic is more extreme than the critical value determined by the appropriate reference distribution, the null hypothesis is rejected. The critical value depends on the significance level of the test (the probability of erroneously rejecting the null hypothesis) measured by the "p" value. That is, if the calculated *t* does not exceed these values, hence the null hypothesis cannot be rejected with 95 percent confidence ($p < 0.05$).

For each wind farm in Europe, MERRA HIRES and ECWMF wind speed time series have been found to be highly correlated between each other with R_{mean} = 0.88-0.89, $R_{minimum}$ = 0.48-0.42 and $R_{maximum}$ = 1.0-1.0 once the results are aggregated at country and NUTS-2 level, respectively. In all cases, HIRES dataset shows a high consistency with the original data (MERRA) with a correlation greater than 0.95. According to these general results, it can be stated that the three datasets represent consistently the broad features of wind patterns on the European continental scale.

Nevertheless, a deeper analysis shows how the details of this broad picture differ when prediction skills are closely compared.

Averaging the correlation by country it is observed that in all cases the $R_{MERRA-ECMWF}$ is very similar with the $R_{HIRES-ECMWF}$ with a difference of R=0.02 (with a level of significance p<0.05). This similarity can suggest that at this level of aggregation, the local effects due to the orography that both ECWMF and HIRES could introduce are smoothed.

On the contrary, by regionalizing from country to NUTS-2, the differences between MERRA, ECMWF and HIRES start being significant. There are regions where the $R_{HIGHRES-ECMWF}$ is higher; that means HIRES and ECWMF capture more variability than MERRA. These results occur in the 20% of the NUTS 2 regions, with the highest correlation of 0.943 and with a difference of R = 0.20. The NUTS 2 with such differences in the correlations are located in Spain, Germany, Greece, Romania, Portugal, Norway and United Kingdom. It is worth to say that those countries have coastal sites and the wind speed is characterised by the sea-breeze interaction effects.

Wind farm sites are extremely heterogeneous across Europe and this result could indicate that HIRES indeed introduces more variability in the dataset although its actual added value in properly asses the local wind effects could differ site by site.

For this reason, site level data have been deeper analysed and in order to crosscheck the variability and the dispersion of the datasets. The measures of the dispersion are the quantities that characterize the spread of the data such as the range, inter-quantile range; the standard deviations and the distance to the mean are calculated.

While low standard deviation indicates a dataset is closer to the mean and has lower variability; high standard deviation shows that data points are spread out over a wider range of values, the dataset is more dispersed. This behaviour can be observed indeed in the boxplots of Figure 10 and the scatter density plots of Figure 9.

A visual comparison of the scatter density plots indicates as the variability is higher and more spread in the case of HIRES (wind speed corrected at site level) and in the ECWMF (wind speed extracted at 12 km x 12 km resolution) with respect to MERRA datasets (70 km x 70 km, approximately). The scatter density plot between MERRA-HIRES (1) shows that the standard deviation of HIRES is more spread and the range is higher than in MERRA, the cloud is shifted upwards to x=y axis and distributed over the first quadrant. In the case of MERRA-ECMWF (2) the pattern is similar to MERRA-HIRES but lower. On the contrary, the comparison between HIRES and ECMWF (3) indicates that HIRES has slightly more spread than ECMWF but less than with MERRA. In this case, the cloud is closer to the x=y axis.

The boxplots represents the average absolute deviation of the dataset, that is, the average of the absolute deviations from a central point is other statistical indicator of the variability. In this case, the central point is the median of the inter-quantile range. The boxplots show the difference of the mean between mean $_{(HIRES-ECMWF)}$ and mean $_{(MERRA-ECMWF)}$: the negative values indicate that the difference between the mean of HIRES and ECMWF is lower than the mean between MERRA and ECMWF showing that HIRES and contributes with more variability than MERRA. It is also possible to identify that HIRES simulate higher winds than MERRA (negative values are most of the countries) since wind farms are typically built on sites with higher wind resources that are better capture thanks to the statistical downscaling procedure.

The statistical results obtained so far are in line with the physical behaviour of the wind speed variability at different resolutions. The downscaling technique (HIRES) is applied to capture the effect of fine-scale forcing, in particular in areas characterised by fine spatial variability of features such as rugged topography and very diverse land surface conditions. In coarser resolutions (MERRA) these effects are smoothed and the variability of the wind speed is usually underestimated.

A deeper analysis on wind speed improvements would need a dataset other than MERRA and HIRES to be appointed as benchmark, but in this report we have preferred not to use of the ECMWF dataset as benchmark since ECMWF is derived from an operational model and it is not possible to assume that has better quality than reanalysis data as far as wind patterns are represented.

Given that, and since 100 m wind speed observations are generally not available, the only alternative to assess the improvement of the synthetic time series is to compare with the actual wind power generation time series provided by the Transmission System Operators.

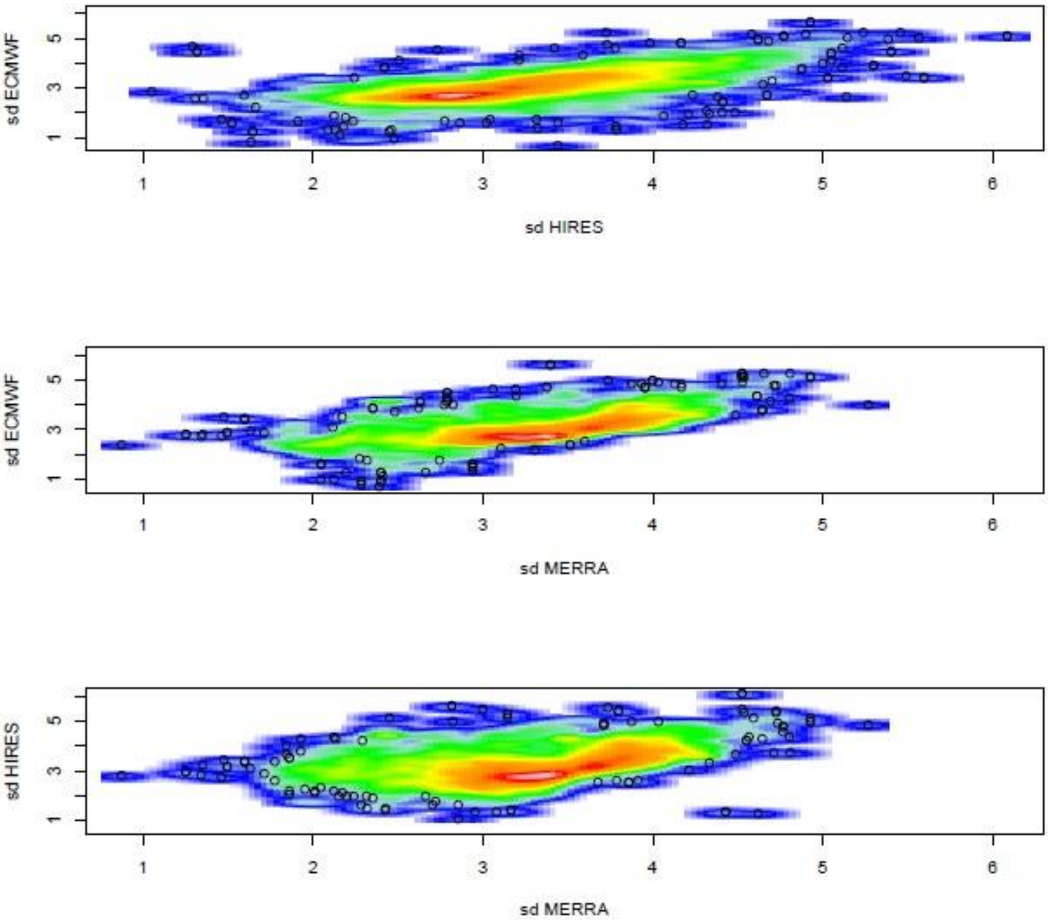

Figure 9 Scatter density plots of the standard deviation of each hourly time series of 2012-2015 for a) MERRA-HIRES, b) ECMWF-HIRES and c) MERRA-ECMWF

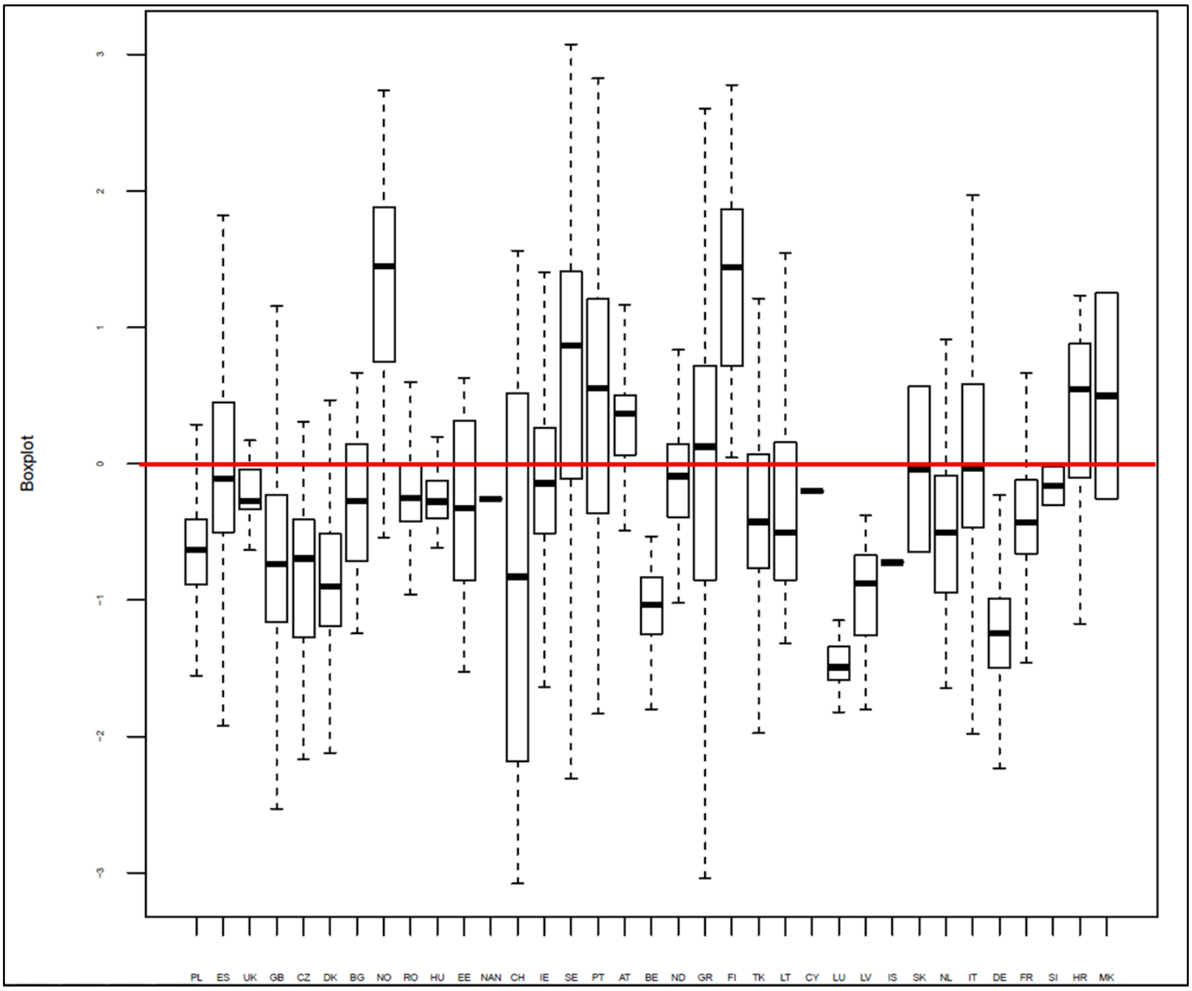

Figure 10 Boxplots of the difference between the mean of MERRA-ECMWF and HIRES-ECMWF grouped by NUTS-1

4.2 Impact of wind speed spatial resolution on power generation at different aggregation levels

The simulated wind power time series (EMHIRES) derived from the HIRES and MERRA wind speed datasets are validated with the actual wind power generation at different aggregation levels using time series and statistics provided by transmission system operators (TSO). Although the time series provided by the TSO are not complete (some of the countries are not available or there are also uncertainties associated to the time series, see section 2.3), they are used as measured values to compare MERRA and EMHIRES.

The validation is firstly assessed by country and bidding zone level, both onshore and offshore. Then, time series are compared at NUTS 2 level with monthly and annual statistics, based on data availability. And finally, the robustness of the high resolution time series is evaluated against the uncertainty level introduced by aggregation of a number of wind farms.

4.2.1 Statistical indicators

The first validation is carried out using hourly time series by country and by bidding zone for 2015. Further, since the bidding zones are smaller regions than country areas (e.g. Norway, Sweden, Denmark and Italy) both aggregation levels are compared to assess the improvement of the HIRES-derived wind power with respect to the MERRA-derived wind power. The statistical performances are summarised in Table 3 and Table 4.

Note that the differences are a source of uncertainty from the method applied to convert wind speed into wind power generation but also because of the errors in the TSO data as shown in Table 2.

The fractional bias (FB) is commonly used for the validation; it measures the mean bias and indicates only systematic error which leads to an underestimation or overestimation of the measured values. It is based on a linear scale and the systematic bias refers to the arithmetic difference between the prediction and the observation. The values range between -2.0 (extreme underprediction) to +2.0 (extreme overprediction). The results indicate that there are no significant differences between the FB associated to MERRA and HIRES by country and by bidding zone. The synthetic time series (MERRA and HIRES) tend to underestimate some countries in other are overestimated but in both datasets the systematic error has a similar level and pattern.

In this analysis, the Pearson's linear correlation coefficient is also calculated to assess the internal consistency of the datasets. In all cases the coefficient indicates that both datasets have good internal consistency since the $R>0.75$ except for Cyprus ($R=0.55$). The wind power time series obtained from HIRES show a better correlation than MERRA in Belgium, Germany, Denmark, Estonia, Finland, France, Hungary, Lithuania, Latvia, Netherlands and Portugal and for the bidding zones of Norway (NO4), Sweden (SW1), Italy (SUD, SICI) and Denmark (DK2) the HIRES also show an improvement in the internal consistency.

However, a good correlation is only necessary but not sufficient to evaluate the quality of a simulation. Therefore, the mean error (ME), the difference between standard deviations (SD) and the root mean square error (RMSE) are computed to gauge the simulation's accuracy. Indeed, high values of RMSE indicate a high level of non-systematic (i.e., random) discrepancy between the simulations and the observations. In addition to that, it is assessed and compared the ability of MERRA and HIRES to reproduce the actual wind power generation time series. For that, the statistical performances need to accomplish the following criteria defined by [34]: (1) the synthetic and real standard deviations are similar; (2) the RMSE are lower than the standard deviation and (3) the unbiased RMSE ($RMSE_{ub}$) which represents the accuracy of the MERRA and HIRES is also lower than the standard deviation.

$$FB = \frac{\sum_i (Xi_{obs} - Yi_{simu})}{0.5 * \sum_i (Xi_{obs} + Yi_{simu})} \quad (16)$$

$$ME = \frac{X_i - Y_i}{n} \quad (17)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_i - Y_i)^2}{n}} \quad (18)$$

$$RMSE_{ub} = \sqrt{\frac{\sum_{i=1}^{n} ((X_i - \bar{X}) - (Y_i - \bar{Y}))^2}{n}} \quad (19)$$

On the bases of these criteria, the results (presented in Table 5) indicate that both datasets, MERRA and EMHIRES, are well characterised by high internal consistency, they are accurate and have the skill of the statistics to be good synthetic time series, and that both datasets have very similar performance.

Nevertheless, the added value provided by the better wind speeds spatial resolutions of HIRES, becomes evident when observing the type of the errors and that most of the countries and bidding zones experience an improvement in EMHIRES with respect to MERRA data. Over the 25 countries and 16 bidding zones analysed, all of them except for Cyprus, Czech Republic, Spain, Poland, Switzerland, and Italy-NORD bidding zone and Italy-SARD bidding zone have better internal consistency, or they are more accurate when EMHIRES series are considered with differences in the standard deviations, the ME, MSE, RMSE or RMSE improving with respect to MERRA.

Moreover, although EMHIRES is more variable and dispersed than MERRA (Figure 9), it has lower differences with respect with the actual values. In the cases EMHIRES time series don't improve with respect to MERRA time series, the errors and the quality of the time series are similar comparing with the TSO data. They have very similar results and in no case EMHIRES visibly worsen the time series with respect to the TSO-time series.

Table 4 Statistical performance of EMHIRES in 2015 using MERRA (first table) and HIRES (second table) dataset by country; green colour indicates the cases which HIRES improves with respect to MERRA

MERRA 2015									
COUNTRY	FB	R	SD TSO	SD MERRA	Delta SD	ME	MSE	RMSE	RMSEub
AT	-0.020	0.904	524.542	598.331	-73.789	11.567	65697.112	256.314	256.053
BE	0.113	0.937	259.638	224.658	34.980	-29.834	9438.977	97.154	92.462
BG	1.138	0.759	141.445	39.745	101.700	-108.687	24292.288	155.860	111.781
CY	0.709	0.436	19.413	11.332	8.081	-10.688	419.812	20.489	17.724
CZ	-0.039	0.920	55.849	75.805	-19.955	2.709	1060.815	32.570	32.459
DE	-0.039	0.971	6687.221	6824.144	-136.923	315.765	2718445.078	1648.771	1619.338
DK	0.001	0.952	808.988	760.422	48.565	-0.524	61210.508	247.408	247.407
EE	-0.021	0.913	55.209	56.807	-1.598	1.548	553.216	23.521	23.470
ES	-0.064	0.916	3234.007	4647.364	-1413.357	364.868	4657755.621	2158.183	2127.118
FI	-0.083	0.929	170.375	230.419	-60.044	20.427	9596.317	97.961	95.808
FR	-0.062	0.952	1516.446	1803.049	-286.603	141.977	365350.483	604.442	587.531
GR	0.082	0.816	304.577	342.580	-38.003	-31.797	40827.701	202.059	199.541
HR	0.322	0.788	79.815	87.462	-7.647	-24.949	3635.836	60.298	54.894
HU	0.288	0.897	77.485	61.996	15.489	-19.580	1610.869	40.136	35.183
IE	0.330	0.949	544.196	412.904	59.291	-215.108	86903.214	294.078	201.068
IT	NA	NA	NA	1461.443	NA	NA	NA	NA	NA
LT	0.213	0.923	76.294	61.686	14.608	-15.721	1203.095	34.686	30.932
LU	NA	NA	NA	8.464	NA	NA	NA	NA	NA
LV	-0.004	0.905	11.479	10.064	1.415	0.050	23.952	4.894	4.894
MT	NA	NA	NA	NA	NA	NA	NA	NA	NA
NL	0.415	0.949	743.259	486.083	257.176	-333.943	220064.470	469.110	332.425
PL	-0.002	0.967	988.485	1014.189	-25.704	2.714	66533.153	257.940	257.931
PT	0.199	0.824	985.643	972.427	13.216	-234.306	392742.957	626.692	581.243

RO	0.278	0.838	671.968	539.686	132.282	-183.912	169105.197	411.224	367.985
SE	-0.083	0.866	1070.392	1685.995	-615.603	164.485	868442.411	931.903	917.686
SI	-0.458	NA	0.376	15.881	-15.505	0.101	0.220	0.469	2.526
SK	NA	NA	NA	NA	NA	NA	NA	NA	NA
UK	-0.055	0.952	1641.242	1772.790	131.452	147.367	291903.137	540.317	540.007
CH	-0.597	0.581	5.921	13.528	-7.606	5.105	151.807	12.321	11.214
NO	NA	NA	NA	146.316	NA	NA	NA	NA	NA
EMHIRES 2015									
COUNTRY	FB	R	SD TSO	SD EMHIRES	Delta SD	ME	MSE	RMSE	RMSEub
AT	0.042	0.869	524.542	551.486	-26.945	-23.241	77128.080	277.719	276.745
BE	0.014	0.947	259.638	284.106	-24.468	-3.970	8462.950	91.994	91.911
BG	1.147	0.733	141.445	41.025	100.420	-109.222	24359.884	156.077	111.586
CY	0.872	0.427	19.413	10.227	9.186	-12.395	463.727	21.534	17.783
CZ	-0.129	0.904	55.849	91.455	-35.605	9.373	2279.732	47.747	46.820
DE	-0.149	0.972	6687.221	9009.699	-2322.477	1264.949	10048056.536	3169.867	2907.804
DK	-0.069	0.957	808.988	894.194	-85.206	72.502	75409.522	274.608	264.864
EE	-0.052	0.920	55.209	61.263	-6.054	3.813	593.795	24.368	24.068
ES	-0.069	0.913	3234.007	4721.685	-1487.678	393.357	5035397.749	2243.969	2209.224
FI	-0.027	0.944	170.375	191.459	-21.083	6.485	4166.354	64.547	64.221
FR	-0.076	0.959	1516.446	1908.122	-391.676	176.804	423205.598	650.543	626.056
GR	0.076	0.813	304.577	342.959	-38.382	-29.684	41352.686	203.354	201.176
HR	0.322	0.814	79.815	82.715	-2.899	-24.949	3087.804	55.568	49.652
HU	0.288	0.876	77.485	67.011	10.474	-19.560	1781.545	42.208	37.542
IE	0.33	0.951	544.196	417.304	127.891	-215.121	84922.906	291.677	196.468
IT	NA	NA	NA	1388.701	NA	NA	NA	NA	NA
LT	0.214	0.926	76.294	66.765	9.529	-15.814	1105.297	33.246	29.262
LU	NA	NA	NA	11.252	NA	NA	NA	NA	NA
LV	-0.004	0.921	11.479	11.903	-0.425	0.050	21.880	4.678	4.677

MT	NA	NA	NA	NA	NA	NA	NA	NA	NA
NL	0.417	0.960	743.259	519.334	223.926	-335.311	199063.276	446.165	297.441
PL	-0.073	0.965	988.485	1202.907	-214.422	91.853	138273.770	371.852	360.332
PT	0.110	0.846	985.643	1108.553	-122.910	-135.265	370750.149	608.893	593.678
RO	0.280	0.836	671.968	570.567	101.401	-185.109	170056.188	412.379	368.715
SE	-0.093	0.885	1070.392	1649.465	-579.073	184.156	760495.511	872.064	852.750
SI	-0.579	NA	0.376	12.044	-11.668	0.138	0.263	0.513	1.973
SK	NA	NA	NA	NA	NA	NA	NA	NA	NA
UK	0.0288	0.947	16410.242	14852.727	29.515	-67.606	7350363.546	857.050	530.932
CH	-0.598	0.545	5.921	14.019	-8.097	5.112	168.060	12.964	11.914
NO	NA	NA	NA	124.174	NA	NA	NA	NA	NA

Table 5 Statistical performance of EMHIRES in 2015 using MERRA dataset by bidding zone; the green underlined indicates the cases which HIRES improves with respect to MERRA

MERRA 2015									
Bidding zone	**FB**	**R**	**SD TSO**	**SD MERRA**	**Delta SD**	**ME**	**MSE**	**RMSE**	**RMSEub**
NO1	NA	NA	NA	0.258	NA	NA	NA	NA	NA
NO2	-0.071	0.865	63.342	94.345	-31.003	6.539	2547.095	50.469	50.048
NO3	0.816	0.556	92.330	76.020	16.310	-63.451	10540.006	102.665	80.710
NO4	0.188	0.682	39.722	39.570	0.151	-10.784	1084.710	32.935	31.127
NO5	1.980	0.552	6.981	0.047	6.934	-7.727	108.074	10.396	6.955
SW1	0.147	0.755	125.280	183.608	-58.329	-22.184	15099.146	122.879	120.868
SW2	-0.121	0.859	403.387	646.844	-243.457	72.870	138019.911	371.510	364.319
SW3	-0.274	0.886	464.958	1042.507	-577.548	219.714	476194.836	690.069	654.410
SW4	-0.053	0.952	341.954	416.827	-74.873	25.843	19246.082	138.730	136.479
CNOR	0.231	0.660	22.947	29.000	-6.053	-4.831	512.704	22.643	22.122
NORD	0.237	0.592	5.885	6.250	-0.366	-1.284	31.778	5.637	5.489
SARD	0.270	0.711	190.754	214.751	-23.998	-40.443	25867.336	160.833	155.665
SUD	-0.140	0.795	692.715	1229.679	-536.964	133.218	656086.483	809.992	798.962
CSUD	-0.079	0.768	273.677	444.336	-170.659	22.844	86024.785	293.300	292.409
SICI	-0.078	0.837	312.417	461.454	-149.038	24.550	69774.549	264.149	263.005
DK1	0.032	0.948	692.582	628.604	63.978	-27.402	50523.155	224.774	223.097
DK2	-0.017	0.940	133.755	128.797	4.958	2.678	2103.306	45.862	45.784
EMHIRES 2015									
Bidding zone	**FB**	**R**	**SD TSO**	**SD EMHIRES**	**Delta SD**	**ME**	**MSE**	**RMSE**	**RMSEub**
NO1	NA	NA	NA	0.543	NA	NA	NA	NA	NA
NO2	-0.024	0.848	63.342	81.501	-18.159	2.184	1861.581	43.146	43.094
NO3	0.865	0.551	92.330	65.329	27.001	-66.108	10519.286	102.564	78.416
NO4	0.229	0.696	39.722	32.643	7.079	-12.900	996.852	31.573	28.821

NO5	1.968	0.543	6.981	0.058	6.923	-7.703	107.630	10.375	6.949
SW1	0.290	0.762	125.280	141.753	-16.474	-41.064	10371.179	101.839	93.201
SW2	-0.077	0.856	403.387	576.009	-172.622	45.263	99517.476	315.464	312.205
SW3	-0.194	0.910	464.958	813.475	-348.516	148.492	204143.690	451.823	426.993
SW4	-0.032	0.938	341.954	409.506	-67.552	15.277	21808.952	147.679	147.020
CNOR	0.258	0.594	22.947	30.582	-7.635	-5.333	656.053	25.614	25.052
NORD	0.184	0.594	5.885	7.057	-1.173	-1.018	36.138	6.011	5.925
SARD	0.281	0.708	190.754	215.964	-25.210	-41.933	26476.884	162.717	157.221
SUD	-0.094	0.801	692.715	1073.946	-381.231	86.915	449546.564	670.482	664.825
CSUD	0.137	0.758	273.677	319.409	-45.732	-35.380	45646.646	213.651	210.701
SICI	-0.088	0.849	312.417	464.277	-151.860	27.758	67678.337	260.151	258.665
DK1	-0.026	0.948	692.582	740.647	-48.065	22.746	55816.926	236.256	235.159
DK2	-0.099	0.945	133.755	152.700	-18.945	15.860	2854.196	53.425	51.016

4.2.2 Duration curves and boxplots

Wind power duration curves and boxplots for MERRA, EMHIRES and TSO data are shown in Figure 11, Figure 12, Figure 13 and Figure 14. It is observed that for the countries and bidding zones where the EMHIRES statistics are better than MERRA, the cumulative distributions are closer to the TSO data, mainly at the highest wind power values. An example of the statistically significance (Student's t-test) between MERRA and EMHIRES with TSO is indicated in Table 6. The table includes for each pair of datasets the t indicator and the p.value, showing that in all cases the datasets follows a Student's t-distribution under the null hypothesis.

In general, there is overestimation in the MERRA and EMHIRES time series due to the installed capacity considered for the power conversion, dated at the end of 2015. The difference may also be due to curtailment and maintenances of the wind farms and because of the uncertainty associated of the methodology. It also worth reminding that, ENTSO-E time series contain inconsistencies as described in section 2.

Although ECWMF dataset contains data from 2012-2015 and it is not suitable for EMHIRES (since the purpose is to release 30 years of wind power generation) ECMWF wind speed of 2015 has been also converted into wind power to be compared with the EMHIRES and MERRA statistical performance. The parameters evaluated show similar skills in the three datasets. As mentioned in the previous section, ECMWF introduces more variability and dispersion than MERRA and the EMHIRES more than the rest all of them, maintaining similar correlations and types of errors with respect the TSO-time series.

Table 6 Example of the Student's t-test summary for EMHIRES and TSO datasets

Country	t	p.value	Country	t	p.value
AT	-2.86	4.27E-03	HU	-20.47	5.24E-92
BE	0.07	9.42E-01	IE	-0.06	9.55E-01
BG	-10.28	1.59E-24	LT	-13.55	1.24E-41
CY	-1.11	0.269079	LV	0.26	7.97E-01
CZ	8.59	9.96E-18	NL	-0.02	9.88E-01
DE	11.25	2.93E-29	PL	5.61	2.10E-08
DK	-0.7	0.482248	PT	-8.53	1.52E-17
EE	4.4	1.10E-05	RO	-17.86	1.11E-70
ES	6.46	1.08E-10	SE	9.92	4.19E-23
FI	2.32	2.06E-02	SI	15.44	5.42E-53
FR	6.77	1.36E-11	SK	71.57	0
GR	-6.12	9.83E-10	UK	-10.36	4.49E-25
HR	-20.32	1.04E-90	CH	30.74	1.08E-199

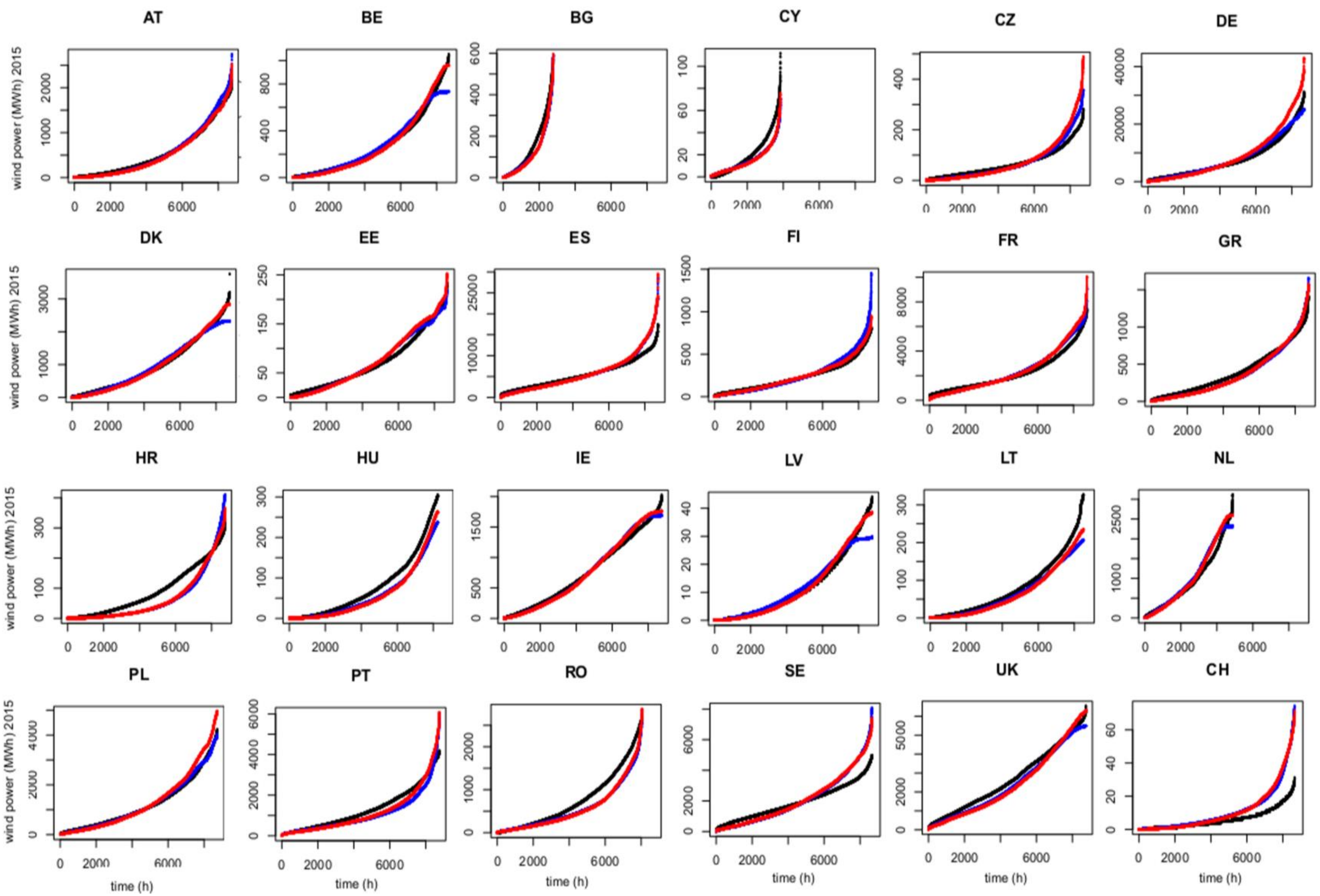

Figure 11 EMHIRES (red), MERRA (blue) and ENTSO-E (black) wind power duration curves for 2015 by country

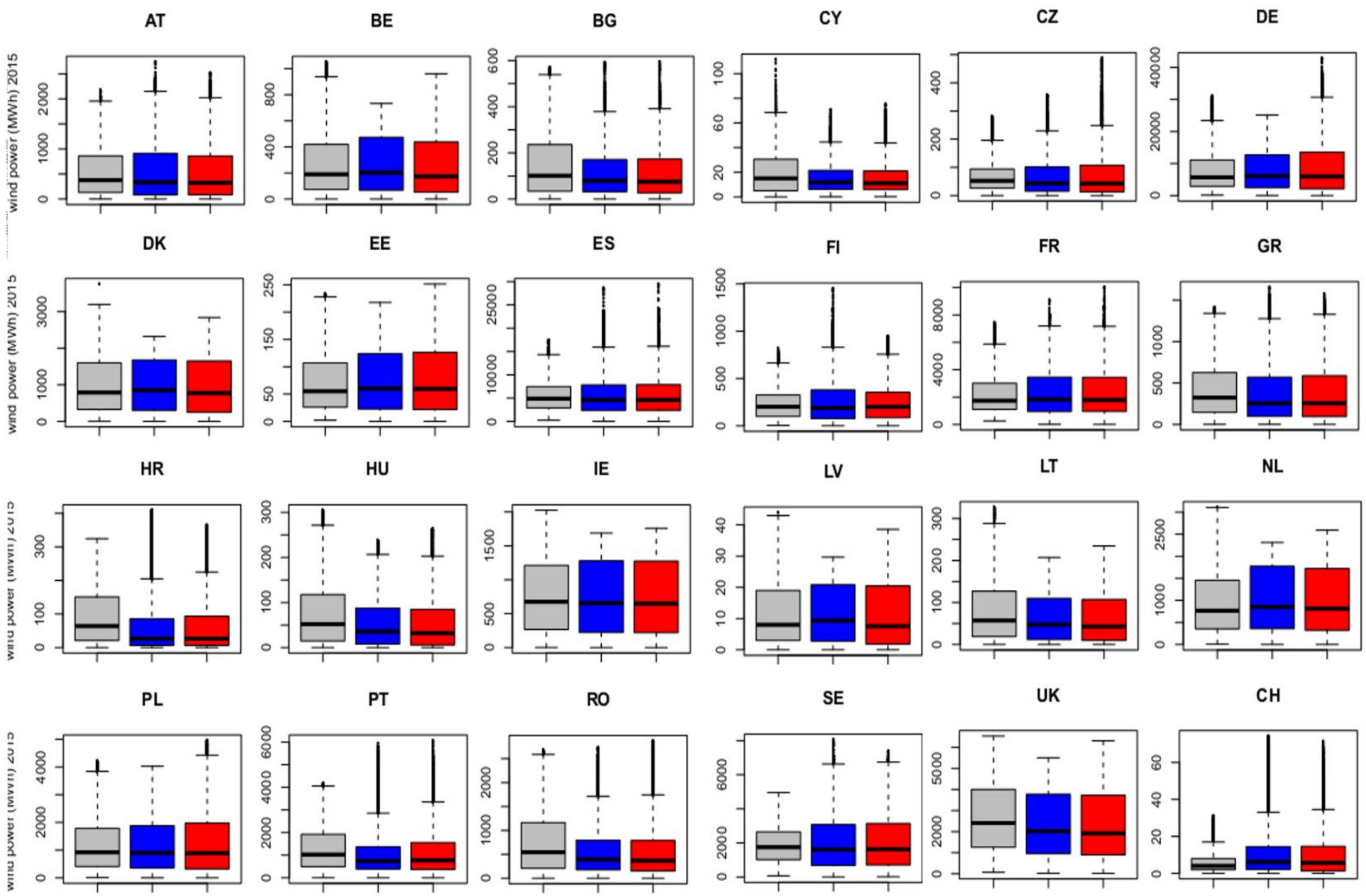

Figure 12 EMHIRES (red), MERRA (blue) and ENTSO-E (grey) boxplots for 2015 by country

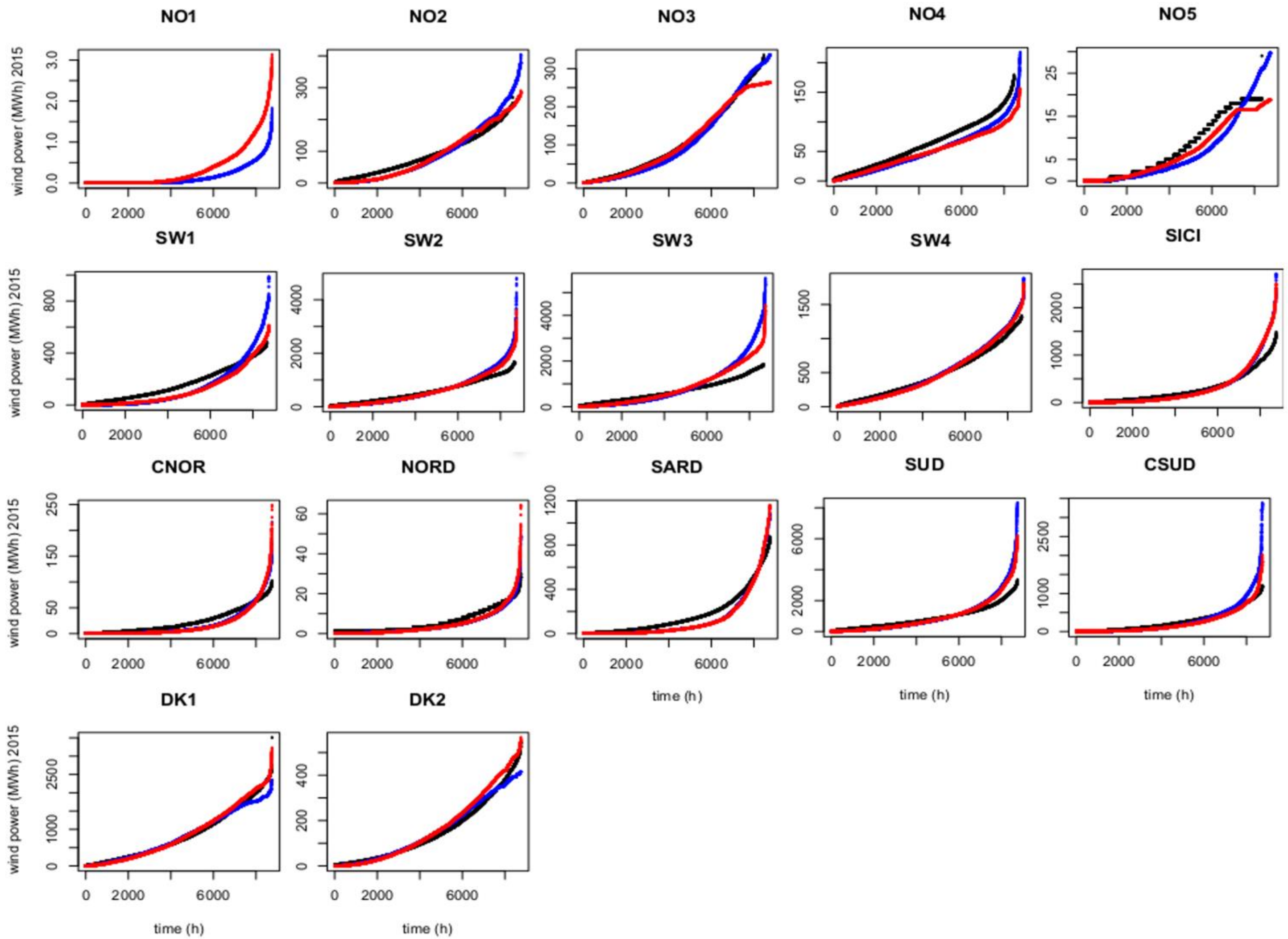

Figure 13 EMHIRES (red), MERRA (blue) and TSO (black) derived wind power duration curves for 2015 by bidding zone

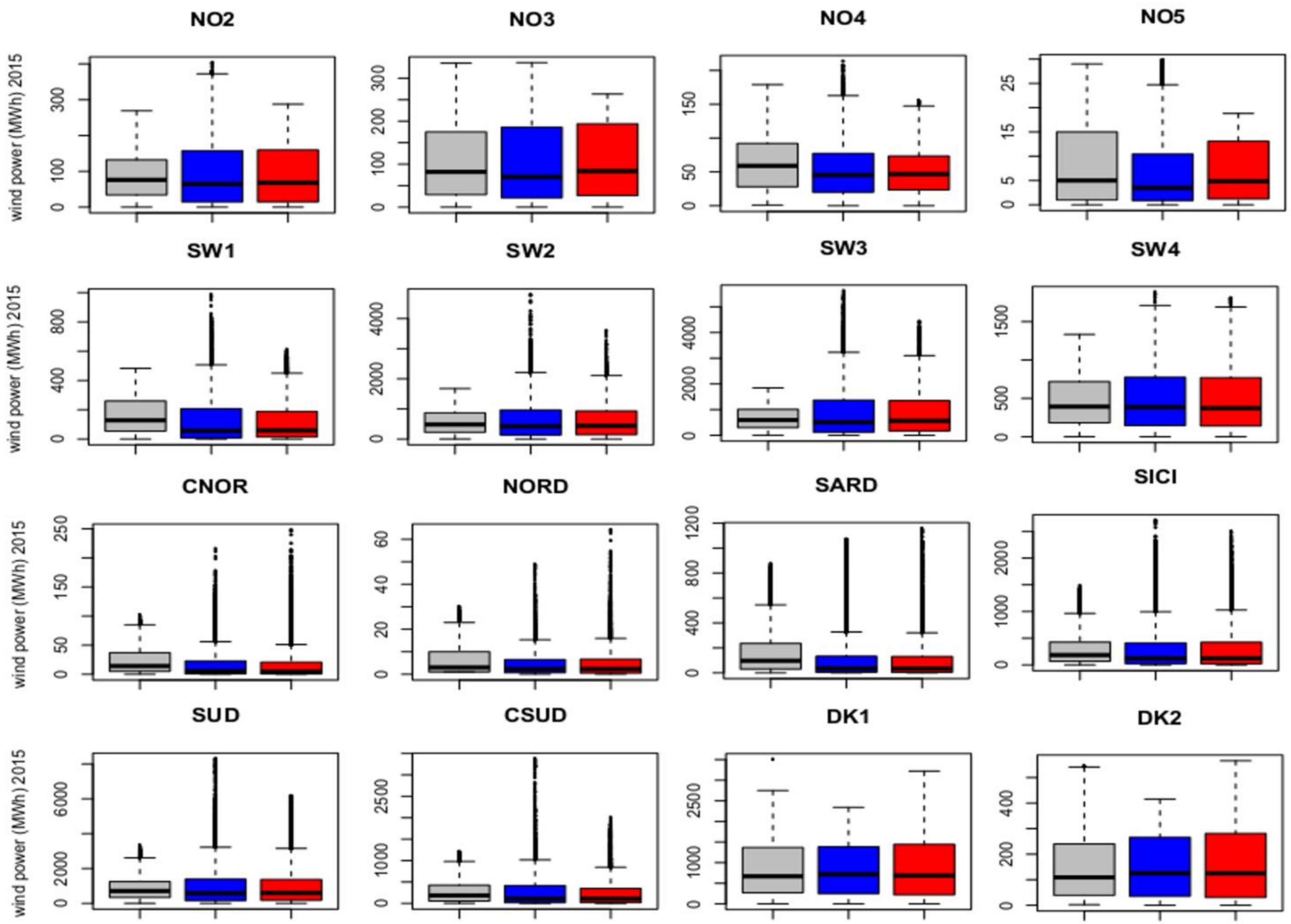

Figure 14 EMHIRES (red), MERRA (blue) and TSO (black) derived wind power boxplots for 2015 by bidding zone

4.2.3 Time series and ramping rates

The overall statistical performance shows good results in all datasets, which means that they are able to reproduce the wind power generation with similar errors. However, EMHIRES incorporates higher variability improving the wind power time series.

Apart from the statistical analysis shown so far, the direct comparison of modelled and measured power curves can provide useful information on the suitability of synthetic time series in reproducing actual data. For instance, Figure 16 represents the wind power generation time series of the three datasets (ENTSO-E, MERRA and EMHIRES) for Denmark. It is observed that MERRA is not able to reproduce the wind power generation peaks as well as EMHIRES. The difference results from the spatial resolutions of the wind speed; the coarser resolution is not able to reproduce the variability and local effects of the wind speed. Those effects are smoothed and the main consequence is the underestimation of the wind power peaks.

This behaviour is more pronounced when the time series are more spatially disaggregated; for example, by bidding zones in Denmark (DK1 and DK2). In those cases the improvement of the EMHIRES is more significant (Figure 17 and Figure 18). Figure 19, Figure 20 and Figure 21 are other examples of this behaviour. Although in other cases EMHIRES overestimates the peaks of wind power generation, the statistical analysis indicate that the contribution to the uncertainty is lower than the improvement of the results.

On the physical basis, the results show that the increased power from EMHIRES may be the overall effect of wind turbines being sited in favourable locations with speed up due to orographic or roughness effects, which are captured by Global Wind Atlas predicted wind climate data, but not by MERRA. Also increased variability can be captured because these effects are locally a function of wind direction. This effect can be observed at country and by bidding zone aggregation levels.

In order to assess the quality of EMHIRES in capturing the sudden increase or decrease of power characterised by large positive or negative hour by hour differences, the ramp rate distribution is calculated. The following plots (Figure 15) show the frequency distribution of the difference between the power production at hour (h) and at (h-1), namely ($WP_{t-(t-1)}$) in the countries with significant installed capacity (Spain, Denmark, United Kingdom and Germany).

The histograms represent the TSO data, divided into 100 intervals in order to take into account the minimum and maximum power difference. The distribution curves correspond to EMHIRES (red) and MERRA (blue). The range of the plot is ±10000 MWh in order to compare the ramping rates peaks of all countries considered. In general, the distribution of MERRA is steeper in the "bell" and less prolonged in the "edges" of the distribution than EMHIRES. This reflects the underestimation of the wind speed due to smoothing, i.e. not taking into account the local effects at the sites of the wind farms. It can be seen that the ramping rates of EMHIRES are better representing the TSO data.

In the case of Denmark, the most frequent ramping rates occur in an interval of a $WP_{t-(t-1)}$ -600 to 600 MWh (95% confidence interval). Both cases, MERRA and EMHIRES are able to capture the negative ramping rates in the 99.5% of the hours. In the case of large sudden positive increases (out of the 95% interval), EMHIRES improves with respect to MERRA. MERRA is not able to capture differences greater than 600 MWh while EMHIRES is able to reproduce 4 ramps that occurred in the range of 600 and 1200 MWh. During the 2015, there were 2 hours with a positive increases of 1200 MWh and 1800 MWh respectively that neither dataset is able to capture.

In the case of Germany and Spain EMHIRES and MERRA slightly underestimate the ramping rates with respect to the TSO. In Germany, the 95% confidence interval of ramping rates occur mainly between -1000 to 2000 MWh, and the datasets capture the sudden changes in a 92% of the hours. For Spain, the 95% confidence interval is between -2000 to 2000 MWh and EMHIRES captures the ramping rated in 97% of the cases. There is one positive maximum of 8000 MWh in Germany and 10000 MWh in Spain and one negative maximum of -6000 MWh and -9000 MWh in Germany and Spain, respectively. Neither EMHIRES nor MERRA are able to capture them.

EMHIRES shows a noticeable improvement with respect to MERRA in the United Kingdom. The 95% confidence interval is between -940 to 1300 MWh redistributed into three different subintervals. That is, there are 340 hours with sudden increase between -940 to -340 MWh and EMHIRES captures 50% of the hours compared with 35% captured by MERRA. There are 7278 ramping rates between -340 to 200 MWh and EMHIRES overestimates the changes in 8% of the cases while MERRA overestimates in 15%. Finally, there are 14 large changes between 700 and 1300 MWh. While MERRA is not able to capture any of these ramps, EMHIRES captures 7 cases. According to the TSO data, the positive and negative maximums occurred once at 6000MWh and at -5000 MWh, this time neither EMHIRES nor MERRA are able to capture them

In summary, EMHIRES shows an improvement with respect to MERRA in the 95% confidence interval of ramping rates during 2015. In addition, EMHIRES also improves in capturing the large negative sudden increases of wind power out of the 95% interval. However, the limitation of the weather derived wind power time series appears when trying to capture the maximum of the ramping rates (1 and 100 percentiles of the ramping rates distributions). EMHIRES (and consequently MERRA) are not able to reproduce some extreme situations since the methodology does not take into account effects of curtailment, outages such as maintenances and grid losses and sudden disruptions.

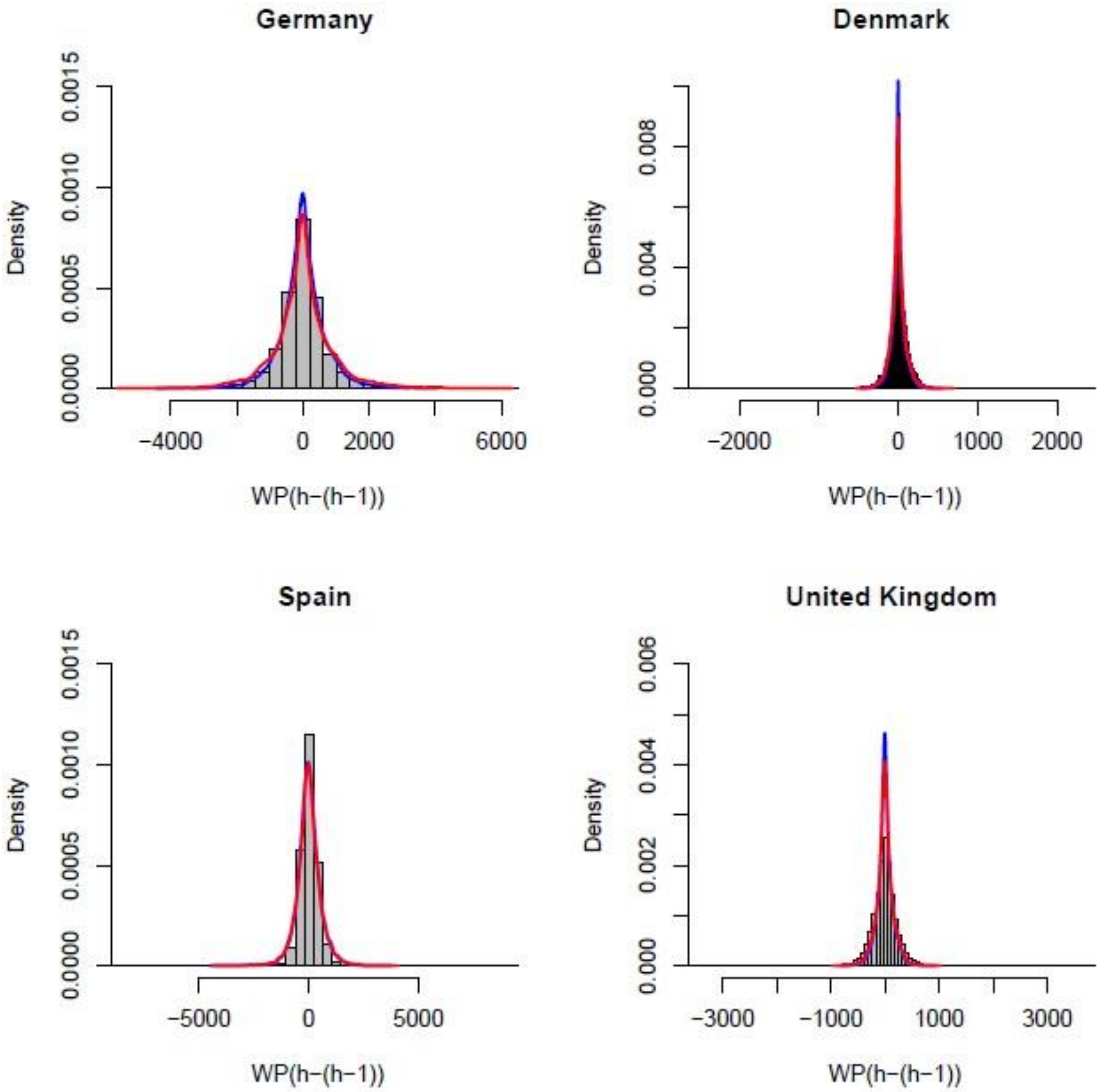

Figure 15 Ramp rate distributions in 2015 for Denmark, Germany, Spain and United Kingdom. TSO data are represented with the grey histograms, EMHIRES (red) and MERRA (blue) are the distribution density curves.

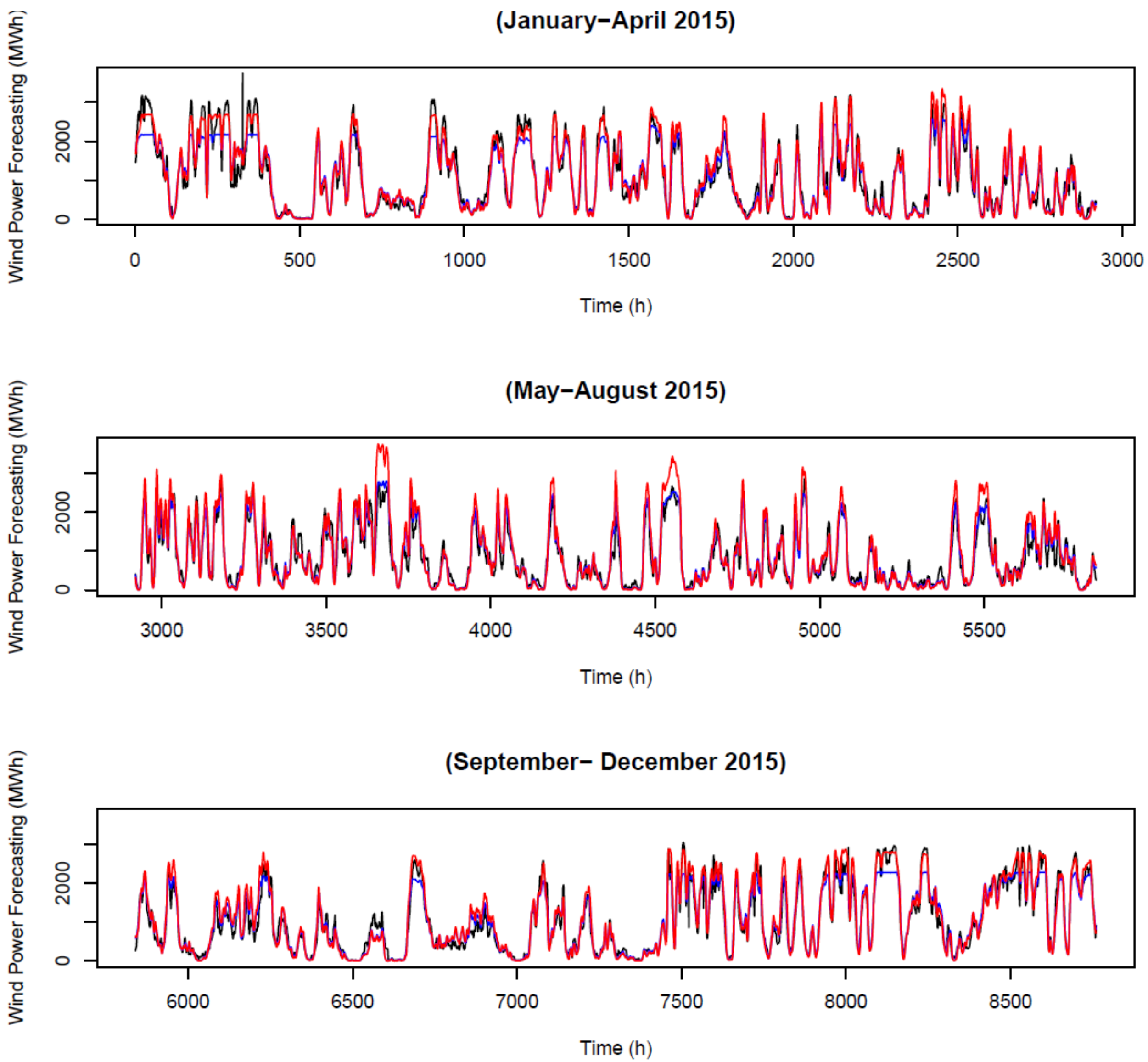

Figure 16 Comparison of the hourly wind power time series for Denmark in 2015

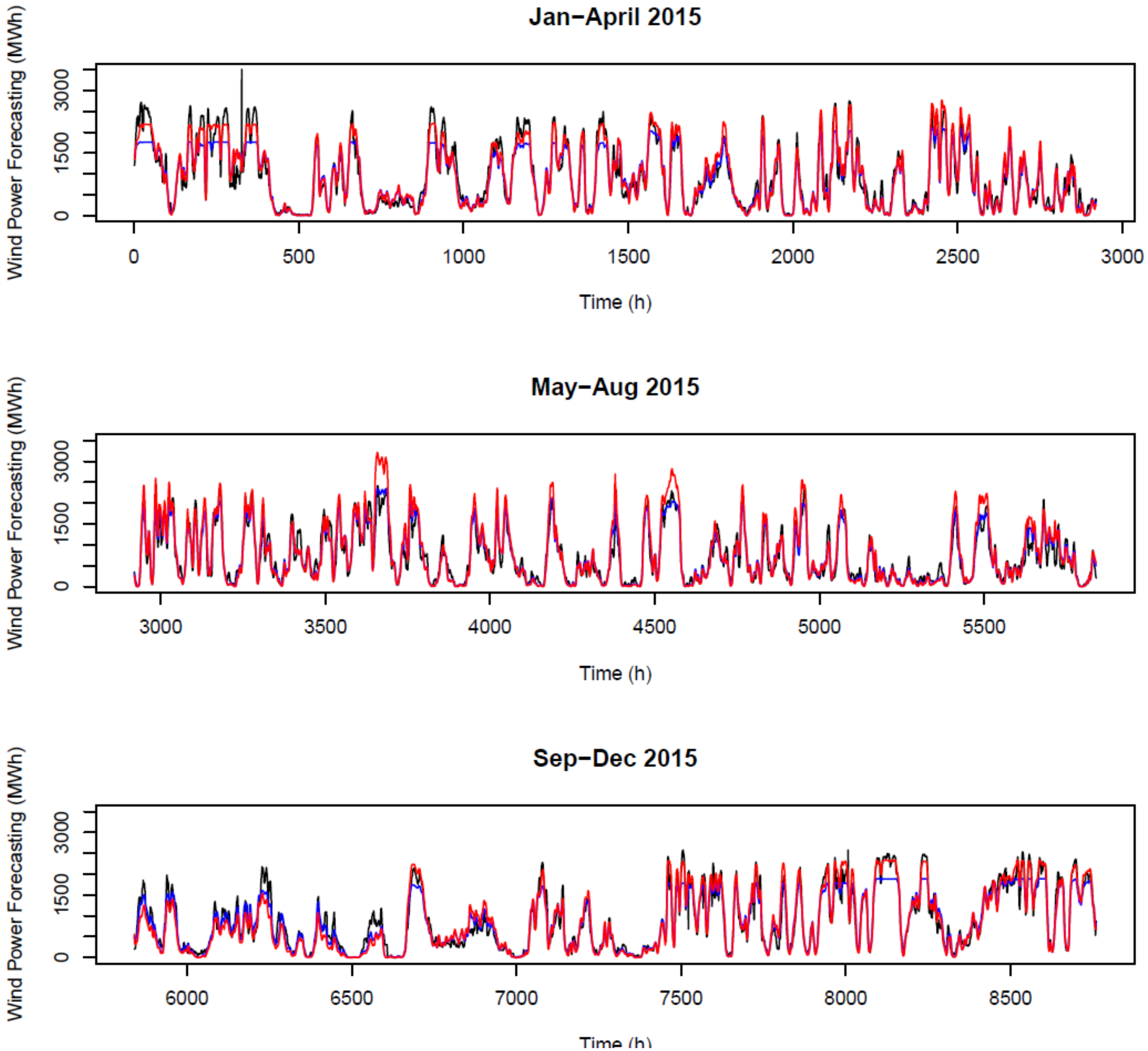

Figure 17 Comparison of the hourly wind power time series for Denmark by bidding zone (DK1)

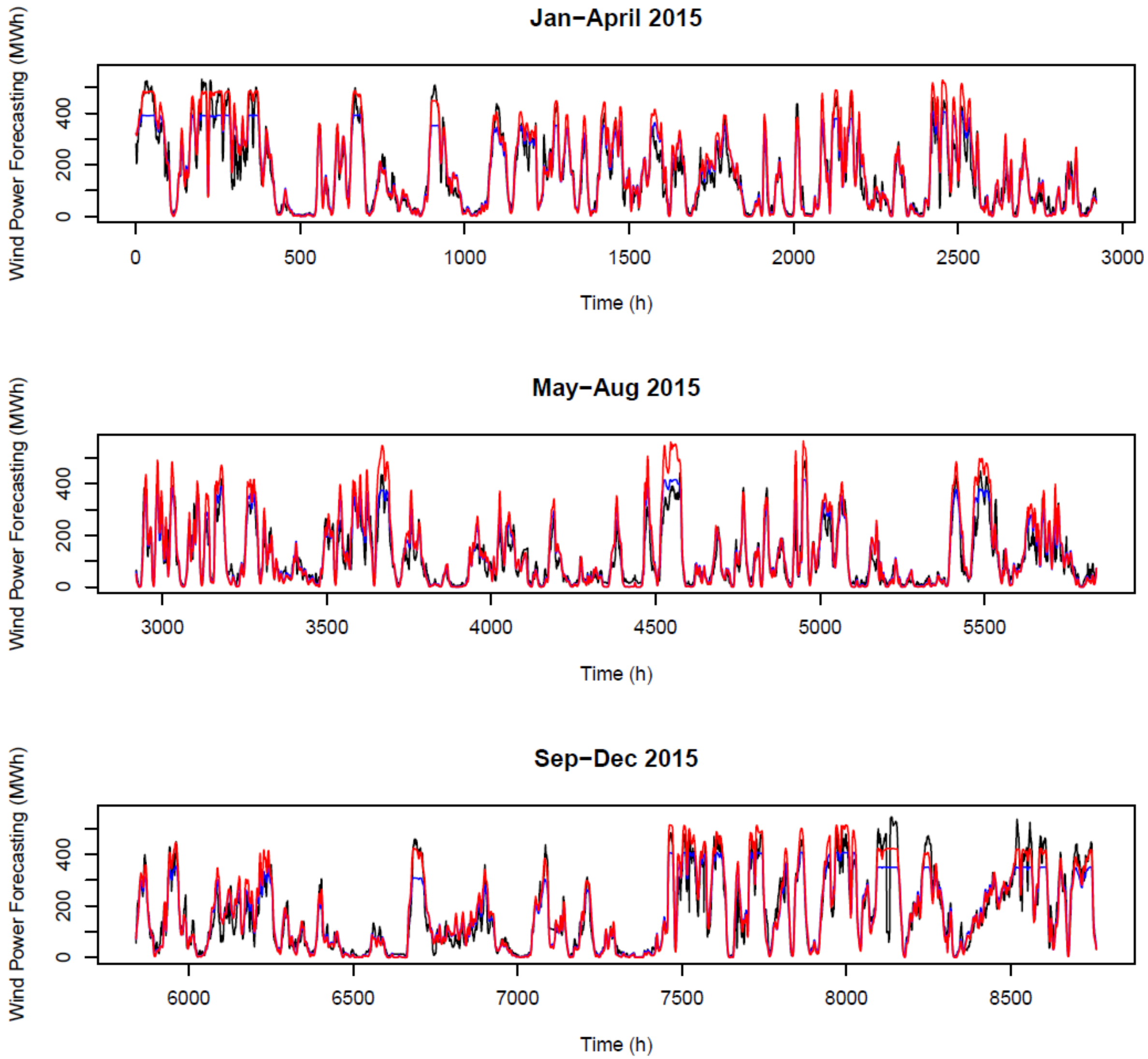

Figure 18 Comparison of the hourly wind power time series for Denmark by bidding zone (DK2)

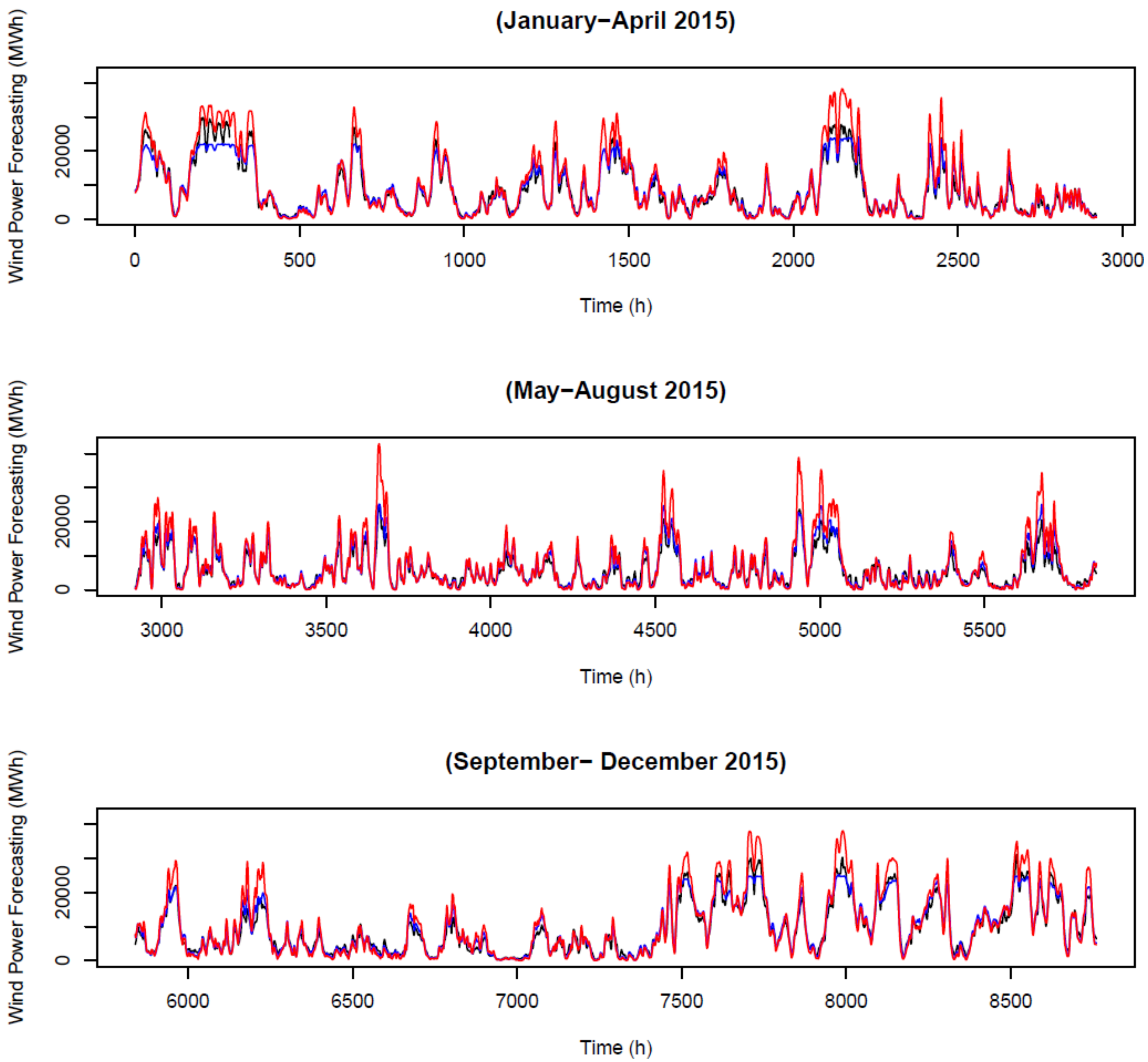

Figure 19 Comparison of the hourly wind power time series for January-April 2015 for Germany

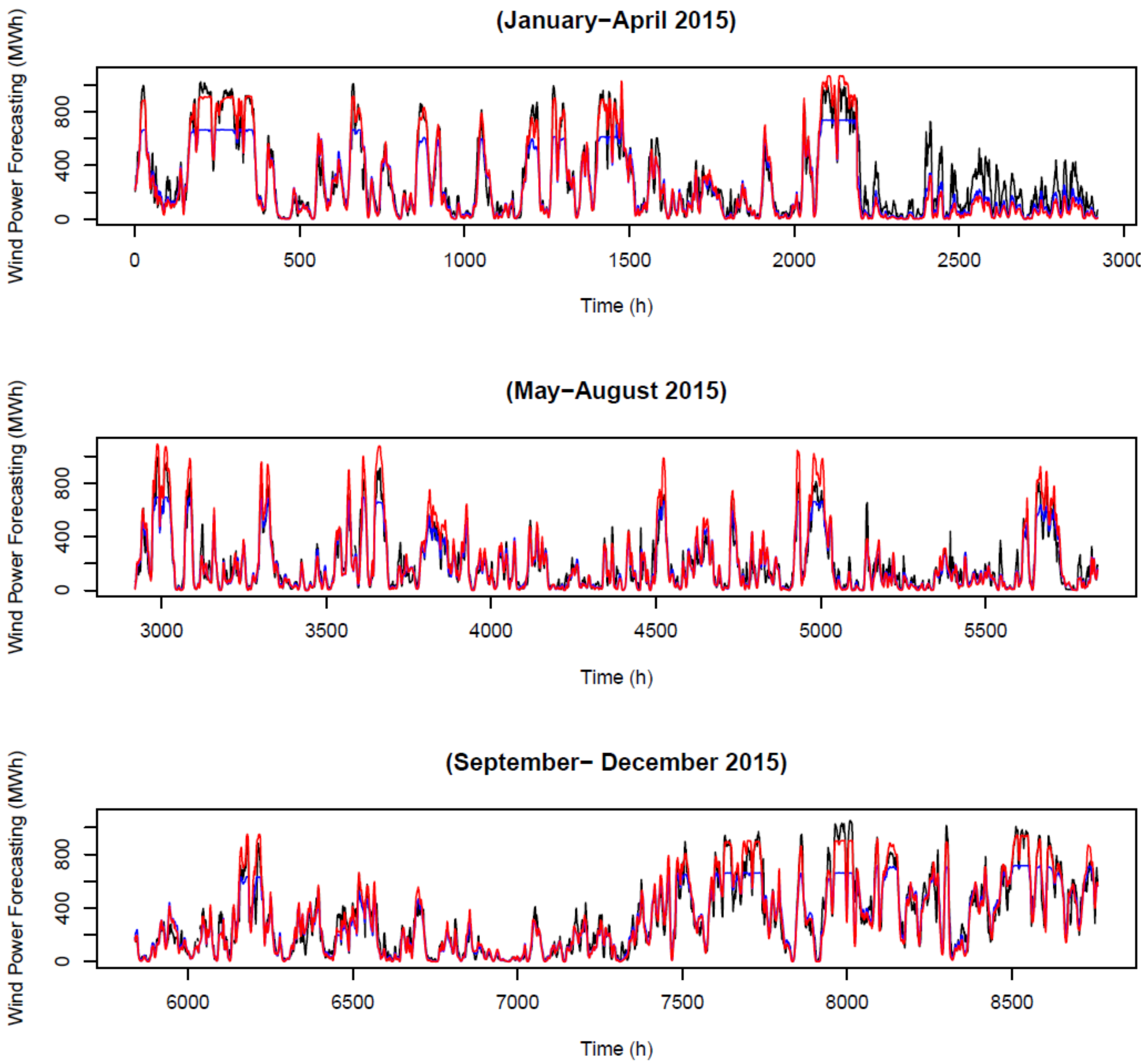

Figure 20 Comparison of the hourly wind power time series for Belgium 2015

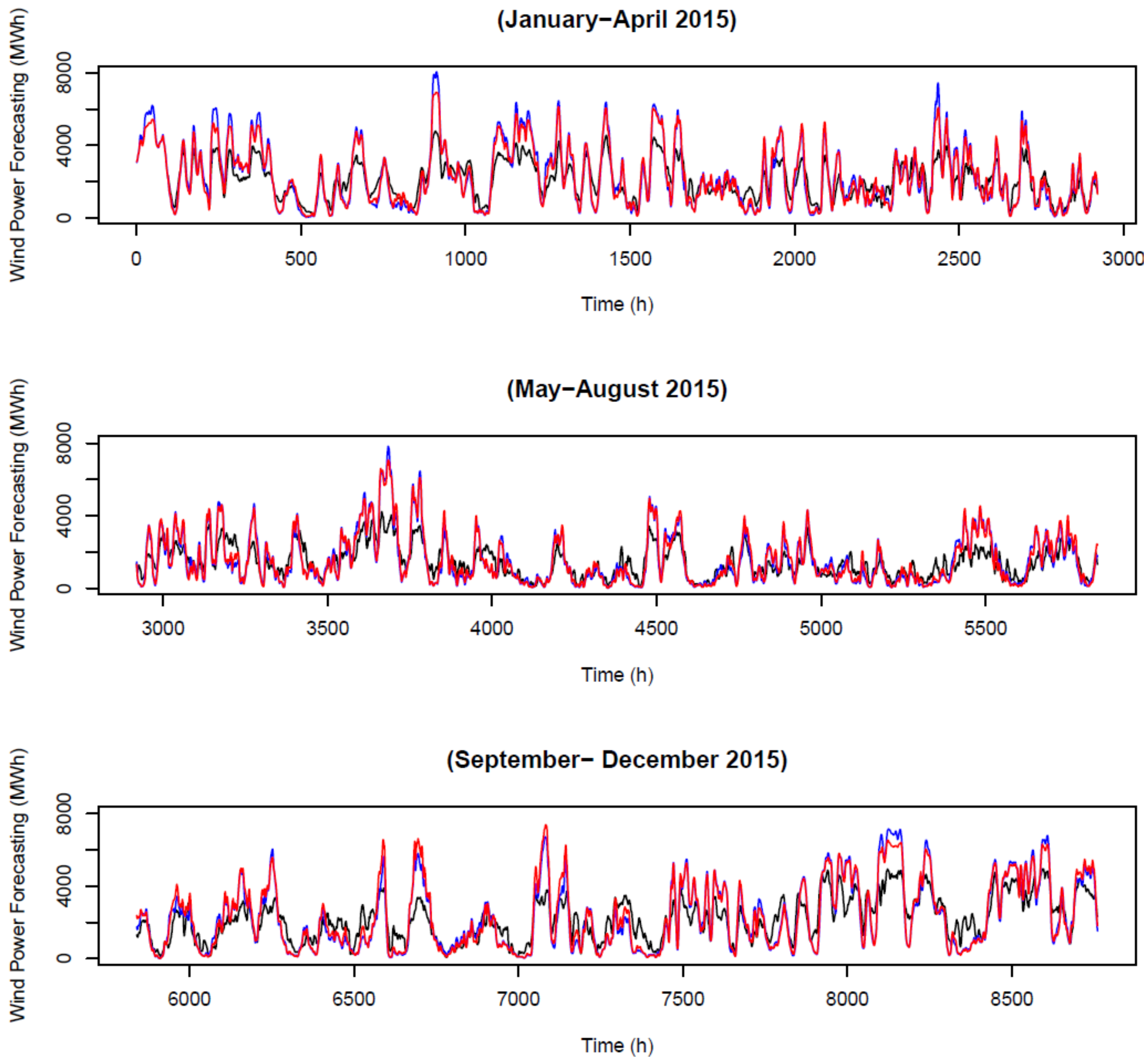

Figure 21 Comparison of the hourly wind power time series for Sweden 2015

4.2.4 Offshore power

The HIRES downscaling technique it is not applied to the offshore wind farms because of lack of orography and roughness and the offshore wind power generation time series are directly produced with MERRA primary data. Off shore time series are released separately for the countries with high installed capacity (Belgium, Denmark, Germany, Netherlands and United Kingdom). The rest of the time series for countries with 1 or 2 offshore wind farms are added to the onshore wind power generation time series.

The validation for the MERRA generated offshore time series also shows the skill of the statistics (Table 7 and Table 8). The bias in the statistics of the offshore is greater than in the onshore. This could be explained because of the sum up of the time series (aggregation level) is too detailed and in those cases the effects not taken into account for the wind power simulation are exacerbated (e.g. the wake effect and the multi-turbine effect). I.e. in the case of Belgium, there are 3 wind farms aggregated; Denmark has 16 wind farms, Germany 13 wind farms, Netherlands 5 wind farms and United Kingdom 28 wind farms. In addition, in the latter, the local climate of the locations is very diverse and it is not very well capture by the MERRA data.

Table 7 Basic statistics for the offshore actual generation provided by ENTSO-E

ENTSOE basic statistics (MWh)							
Country	Min	1st q	Median	Mean	3rd q	Max	NA
BE	0	75	243	294	534	689	96
DK	0	216	533	548	853	123	0
DE	0	279	661	931	1434	2947	48
NL	0	57	139	159	281	363	3723
UK	0	495	1248	1447	2257	4038	0

Table 8 Statistical performance of the offshore wind power generation time series derived from MERRA data

NASA MERRA time series basic statistics for 2015 (MWh)								
Country	FB	R	SD-obs	SD-simu	ME	MSE	RMSE	RMSEub
BE	-0.0048	0.931	234.331	224.9316	1.443	7308.218	85.48811	85.48
DK	0.0016	0.972	359.125	355.4183	-0.879	32635.73	180.6536	180.65
DE	0.118	0.924	803.983	762.3073	-103.74	105589.6	324.945	307.948
NL	-0.05607	0.881	113.117	133.2724	9.2105	3871.889	62.2245	62.32
UK	0.0002	0.229	1091.429	958.5054	-0.425	1629044	1276.34	1276.34

4.2.5 Capacity factors

Additional comparison of the EMHIRES dataset with the TSO time series is done by calculating the total Full Load Hours (FLH); that is, the ratio between the sums of the energy produced (GWh) and the maximum possible generation (installed capacity(GW) *8760h (GWh)) per country. The Table below includes the FLH coefficients for EMHIRES and TSO data showing that both values are hovering the 25%.

Table 9 Capacity factors /full load hours for each country given by EMHIREs and TSO data.

Country	TSO (MW)*8760h	FLH TSO	FLH EMHIRES
Austria	1981	0.22	0.27
Belgium	2172	0.28	0.12
Bulgaria	701	0.23	0.16
Croatia	384	0.23	0.17
Cyprus	155	0.17	0.13
Czech	277	0.23	0.28
Denmark	5082	0.31	0.20
Estonia	301	0.26	0.25
Finland	1082	0.24	0.22
France	10312	0.23	0.23
Germany	43429	0.19	0.21
Greece	1775	0.24	0.21
Hungary	0328	0.23	0.17
Ireland	2400	0.31	0.31
Italy	8750	0.19	0.15
Latvia	070	0.23	0.17
Lithuania	290	0.31	0.23
Luxembourg	60	0.18	0.13
Netherlands	3641	0.22	0.26
Norway	860	0.33	0.24
Poland	5186	0.22	0.25
Portugal	4826	0.26	0.24
Romania	2923	0.27	0.19
Slovakia	3	0.22	0.16
Slovenia	3	0.22	0.27
Spain	23003	0.23	0.25
Sweden	3029	0.62	0.69
Switzerland	60	0.25	0.18
UK	13563	0.20	0.18

4.2.6 Regional statistics

Currently, at NUTS 2 aggregation levels, the only statistics available are the annual total wind power production for Spain, France and Finland. Table 10 presents the comparison of the annual wind power generation by NUTS 2 for the three countries. It is observed that both MERRA and HIRES the total production is similar to the annual statistics except for three NUTS2 in Spain (ES53, ES70, and ES13), three in France (FR10, FR23, FR25) and one in Finland (FI20).

Although in the comparison between MERRA, HIRES and ECMWF the results were highly correlated between the three datasets, it would be necessary to validate the data at regional scale with actual hourly time series. Therefore, the validation by NUTS 2 region will continue once the data is released by the national TSO.

Table 10 Comparison of the annual total wind power generation at NUTS 2 level for Spain, France and Finland

Country	Region defined	NUTS2 code	Annual (GWh)	MERRA (GWh)	HIRES (GWh)
ES	Andalucía	ES61	5781.6	8540.9	10115.0
ES	Aragón	ES24	4127.4	4251.8	4454.4
ES	Asturias	ES12	889.4	847.2	654.9
ES	Comunidad Valenciana	ES52	2172.8	2123.6	1761.9
ES	Cantabria	ES13	58.1	290.9	211.4
ES	Castilla La Mancha	ES42	6940.1	6739.3	5988.9
ES	Castilla León	ES41	10288.5	14665.2	12770.4
ES	Cataluña	ES51	2542.2	2601.7	2501.0
ES	Galicia	ES11	7217.5	4707.2	6991.3
ES	La Rioja	ES23	903.1	837.2	859.7
ES	Murcia	ES62	412.8	503.7	448.9
ES	Navarra	ES22	2551.2	3134.3	3477.2
ES	País Vasco	ES21	293.9	170.2	161.5
FR	Auvergne-Rhône-Alpes	FR72,FR71	799.0	818.8	1065.7
FR	Bourgogne-Franche-Comté / Bourgogne Franche-Comte	FR26,FR43	695.4	330.6	330.7
FR	Bretagne	FR52	1651.0	2712.5	2442.2
FR	Centre-Val de Loire	FR51, FR24	1927.6	3174.3	3261.1
FR	Corse	FR83	24.2	7.1	16.8
FR	Grand-Est / Alsace Champagne-Ardenne Lorraine	FR41, FR42,FR21	5165.7	4031.9	3693.0
FR	Hauts-de-France / Nord-Pas-De-Calais- Picardie	FR30, FR22	4966.2	5484.3	5212.4
FR	Ile-de-France	FR10	52.7	150.1	133.3
FR	Normandie	FR23,FR25	1259.7	4470.5	4261.1
FR	Nouvelle-Aquitaine / Aquitania, Limousin, Poitou-Charentes	FR61, FR63, FR53	924.0	1120.6	1183.7
FR	Occitanie / Languedoc-Roussillon Midi Pyrenees	FR81, FR62	2318.0	1516.3	2332.0
FR	Pays de la Loire	FR51	1223.4	1676.2	1757.5
FR	Provence-Alpes-Côte d'Azur	FR82	105.4	91.6	125.3
FI	Uusimaa	FI1B	11.0	14.8	11.0
FI	Varsinais-Suomi, Kanta-Häme, Päijät-Häme, Kymenlaakso, Etelä-Karjala	FI1C	154.0	278.3	247.1
FI	Etelä-Savo, Pohjois-Savo, Pohjois-Karjala, Keski-Pohjanmaa, Pohjois-Pohjanmaa, Kainuu, Lappi	FI1D	1504.0	1086.6	1042.6
FI	Keski-Suomi, Etelä-Pohjanmaa, Pohjanmaa	FI19	592.0	615.1	604.0
FI	Ahvenanmaa	FI20	65.0	245.9	189.0

4.3 Description of the files generated and platform used

The first version of EMHIRES dataset releases four different files about the wind power generation hourly time series during 30 years (1986-2015), taking into account the existing wind fleet at the end of 2015, for each country (onshore and offshore), bidding zone and by NUTS 1 and NUTS 2 region:

- **EMHIRES_WINDPOWER_ONSHORE_COUNTRY_30yr.txt**
- **EMHIRES_WINDPOWER_OFFSHORE_COUNTRY_30yr.txt**
- **EMHIRES_WINDPOWER_BIDDINGZONE_30yr.txt**
- **EMHIRES_WINDPOWER_NUTS1_30yr.txt**
- **EMHIRES_WINDPOWER_NUTS2_30yr.txt**

The time series are released as hourly capacity factors time series, taking into account the installed power by country, NUTS1, NUTS2, and bidding zone included in the annexes. The installed capacity (MW) by country has been extracted from ENTSO-E annual statistical factsheet; the installed capacity (MW) at NUTS1, NUTS 2 and NUTS 3 has been calculated using the wind farm database and normalized according to the relationship between the ENTSO-E data and the wind farm database by country.

A detailed description of the data obtained will be performed in future reports and publication. In the present report, some basic statistics of the wind power generation for the 30 years by country have been computed and are reported in Table 11

Table 11 Basic statistics of the wind power generation time series for the 30 years by country ONSHORE and OFFSHORE in MWh

Country	25th percentile	Median	Mean	75th percentile	Maximum	Standard deviation
AT	85.1	334.2	570.0	896.0	2104.4	597.9
BE	40.9	143.7	233.8	360.9	848.3	240.1
BE OFFSHORE	56	236.2	279.4	527.8	601	226.6
BG	28.2	79.4	123.1	175.6	629.6	126.5
CH	1.2	5.5	11.7	16.4	60.4	14.7
CY	7.8	15.8	22.6	30.0	157.5	21.7
CZ	11.1	39.4	69.0	99.4	281.5	76.7
DE	1924.5	5673.1	9137.6	13319.4	42829.1	9507.4
DE OFFSHORE	52	158	176	309	369	130
DK	214.9	690.7	964.1	1540.9	3106.1	878.0
DK OFFSHORE	173	443	493	801	1077	348
EE	17.4	56.0	73.2	121.8	204.2	62.5
ES	2679.4	4826.8	6405.9	8545.0	23025.3	5157.6
FI	67.9	166.0	211.9	323.4	686.6	171.5
FR	845.3	1756.0	2419.4	3471.9	8697.9	2034.4
GR	105.5	272.5	384.3	591.3	1541.7	341.8
HR	7.0	31.3	68.7	102.7	365.0	83.0
HU	5.0	30.1	57.4	87.4	264.3	67.1
IE	157.5	433.1	519.9	861.6	1260.7	399.8
IT	316.9	884.4	1464.2	2143.4	7578.3	1519.6
LT	10.7	41.0	64.1	101.3	236.3	64.5
LU	0.6	3.0	7.8	10.4	48.5	10.8
LV	1.5	6.6	10.9	17.6	38.9	11.2
NL	115.2	421.0	572.8	965.1	1584.7	510.7

Country	25th percentile	Median	Mean	75th percentile	Maximum	Standard deviation
NL OFFSHORE	27	118	152	271	377	133
NO	102.2	184.4	201.1	291.0	497.1	118.7
PL	323.2	833.7	1241.8	1847.5	4694.0	1170.1
PT	386.5	788.8	1112.5	1554.3	4610.8	961.8
RO	171.1	401.6	606.9	857.3	2914.6	585.0
SE	545.0	1282.8	1788.0	2648.9	6024.8	1559.6
SI	0.0	0.1	0.4	0.5	3.1	0.7
SK	0.0	0.2	0.5	0.8	2.6	0.6
UK OFFSHORE	539	1205	1369	2157	3048	934.7
UK	685.3	1525.0	1869.0	2848.2	5261.0	1397.7

Terms of use:

This report describes the methodology used to generate EMHIRES and the approach followed to validate the data against the Transmission System Operators time series. It has been described the associate cascade of uncertainties. Therefore, the responsibility how to use, examine the quality of the data for the user's objectives and treat the data available relies on the user.

If you use EMHIRES data in publications, please acknowledge the Knowledge Management Unit, Directorate C Energy, Transport and Climate, Joint Research Centre, European Commission for the dissemination of EMHIRES.

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Link to download the dataset:
https://setis.ec.europa.eu/publications/jrc-setis-reports/emhires-dataset-part-i-wind-power-generation

5 Conclusions and further steps

EMHIRES is the first publically available European wind power generation dataset derived from meteorological sources that is available up to NUTS-2 level. It was generated applying an innovative methodology capturing local geographical information to generate meteorologically derived wind power time series at high temporal and spatial resolution. This allows for a better understanding of the wind resource at the precise location of wind farms.

The validation of EMHIRES against power system statistics and time series published by Transmission System Operators show a clear improvement in the performance with respect to time series not applying an accurate spatial downscaling.

EMHIRES is able to capture the variability of wind energy, in particular peaks and ramps, in a much more accurate way than previous meteorologically derived time series. The limitation of the weather derived wind power time series appears when trying to capture the maximum of the ramping rates. EMHIRES (and consequently other meteorological derived time series) are not able to reproduce some extreme situations since the methodology does not take into account effects of curtailment, outages such as maintenances and grid losses or network incidences. However, using EMHIRES for power system analysis will increase the accuracy of generation adequacy assessments, renewable energy integration studies and market studies for flexibility technologies such as storage.

This is the first part of EMHIRES, covering wind energy production. Further datasets and publications are planned on PV energy and temperature corrected power demand. The EMHIRES PV will be similar to EMHIRES wind, providing hourly PV time series at country, bidding zone, NUTS1 and NUTS 2 levels. It will be produced based on the DG-JRC PV-GIS platform [35].

PV-GIS is an open source online tool to estimate the solar electricity production of a photovoltaic (PV) system. Currently, it gives the annual output power of solar photovoltaic panels. As a photovoltaic Geographical Information System it proposes a google map application that makes it easy to use. The area covered by the calculator is Europe Asia and Africa. This application calculates the monthly and yearly potential electricity generation E [kWh] of a Photovoltaic system with defined modules, tilt and orientation.

The next step is to couple the EMHIRES wind power and PV with PV GIS platform to construct the whole high quality intermittent RES dataset.

All datasets can be reviewed, updated and readapted to new situations in the power system (e.g. the commissioning of new installations) as well as to future RES-E deployment scenarios.

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Appendix

Country	ENTSO-E installed capacity (MW)
Austria	1981
Belgium	2172
Bulgaria	701
Croatia	384
Cyprus	155
Czech	277
Denmark	5082
Estonia	301
Finland	1082
France	10312
Germany	43429
Greece	1775
Hungary	328
Ireland	2400
Italy	8750
Latvia	70
Lithuania	290
Luxembourg	60
Netherlands	3641
Norway	860
Poland	5186
Portugal	4826
Romania	2923
Slovakia	3
Slovenia	3
Spain	23003
Sweden	3029
Switzerland	60
UK	13563

BIDDING ZONE	Installed capacity (MW)
NO1	4.1
NO2	157.2
NO3	305.7
NO4	267.8
NO5	110.0
DK1	4281.6
DK2	1029.4

SW1	350.8
SW2	807.5
SW3	838.9
SW4	1474.1
NORD	177.3
SARD	1043.1
SICI	2784.2
SUD	3656.0
CNOR	128.0
CSUD	1288.6

NUTS1	Installed capacity (MW)
AT1	1836.0
AT2	77.0
AT3	40.0
BE2	1403.0
BE3	769.0
BG3	698.0
BG4	3.0
CH0	60.0
CY0	155.0
CZ0	277.0
DE1	869.0
DE2	1462.7
DE3	39.9
DE4	6407.5
DE5	180.0
DE6	96.5
DE7	1244.9
DE8	3143.2
DE9	9684.0
DEA	4279.6
DEB	2399.4
DEC	209.6
DED	1682.3
DEE	5565.2
DEF	4660.2
DEG	1505.7
DK0	5082.1
EE0	301.0
ES1	3956.2

ES2	3440.0
ES3	148.0
ES4	9310.9
ES5	2413.9
ES6	3547.7
ES7	187.5
FI1	1109.8
FI2	33.0
FR1	77.0
FR2	5225.1
FR3	590.2
FR4	843.2
FR5	1993.7
FR6	506.9
FR7	419.7
FR8	657.0
GR1	146.2
GR2	386.4
GR3	22.9
GR4	1148.7
HR0	384.0
HU1	1.3
HU2	304.2
HU3	22.8
IE0	2400.9
ITC	139.1
ITF	4712.0
ITG	3689.4
ITH	31.8
ITI	177.8
LT00	290.0
LU00	60.0
LV00	70.0
MK00	37.0
NL1	743.0
NL2	1241.9
NL3	1503.6
NL4	152.8
NO0	860.8
PL1	372.5
PL2	1.7

PL3	614.8
PL4	2177.0
PL5	387.3
PL6	1633.9
PT1	4737.1
PT2	44.2
PT3	45.0
RO1	653.4
RO2	1786.6
RO3	335.3
RO4	147.8
SE1	281.8
SE2	1286.4
SE3	1461.1
SI0	3.0
SK	3.0
UKC	451.4
UKD	1227.1
UKE	918.1
UKF	765.2
UKG	0.5
UKH	1425.9
UKI	17.0
UKJ	1125.9
UKK	237.6
UKL	1475.9
UKM	5319.9
UKN	598.1

NUTS2 code	Installed capacity (MW)
AT11	941.3
AT12	915.4
AT13	7.0
AT21	0.5
AT22	76.6
AT31	39.1
AT32	1.2
BE21	116.2
BE22	107.9
BE23	173.3

BE24	21.5
BE25	984.1
BE31	39.7
BE32	334.5
BE33	91.0
BE34	88.1
BE35	215.7
BG31	2.3
BG32	0.0
BG33	314.7
BG34	381.0
BG42	3.0
CH01	9.3
CH02	40.3
CH05	3.0
CH06	7.5
CY00	155.0
CZ02	5.1
CZ03	0.7
CZ04	146.5
CZ05	47.4
CZ06	21.1
CZ07	49.5
CZ08	6.7
DE11	422.3
DE12	141.4
DE13	194.0
DE14	111.2
DE21	129.9
DE22	60.9
DE23	210.5
DE24	330.4
DE25	185.2
DE26	375.3
DE27	170.5
DE30	39.9
DE40	6407.5
DE50	180.2
DE60	96.5
DE71	385.2
DE72	384.8

DE73	474.9
DE80	3143.2
DE91	1165.8
DE92	1723.0
DE93	2607.2
DE94	4187.9
DEA1	458.0
DEA2	988.6
DEA3	1087.9
DEA4	999.9
DEA5	745.1
DEB1	1035.7
DEB2	771.9
DEB3	591.8
DEC0	209.6
DED2	889.8
DED4	476.8
DED5	315.8
DEE0	5565.2
DEF0	4660.2
DEG0	1505.7
DK01	141.7
DK02	843.4
DK03	1519.1
DK04	1788.0
DK05	789.9
EE00	301.0
ES11	3404.0
ES12	513.9
ES13	38.3
ES21	153.3
ES22	969.3
ES23	475.6
ES24	1841.2
ES30	148.0
ES41	5620.9
ES42	3599.4
ES43	90.7
ES51	1220.0
ES52	1189.3
ES53	4.5

ES61	3284.9
ES62	262.7
ES70	187.5
FI19	286.7
FI1B	15.2
FI1C	109.6
FI1D	698.4
FI20	33.3
FR10	77.0
FR21	1811.0
FR22	1585.7
FR23	269.5
FR24	930.5
FR25	283.5
FR26	344.9
FR30	590.2
FR41	796.5
FR42	13.7
FR43	33.0
FR51	616.4
FR52	894.2
FR53	483.0
FR61	1.2
FR62	455.2
FR63	50.6
FR71	171.5
FR72	248.2
FR81	587.4
FR82	49.9
FR83	19.8
GR11	146.2
GR12	33.3
GR13	3.6
GR14	33.9
GR21	16.7
GR22	7.2
GR23	27.4
GR24	272.0
GR25	63.1
GR30	22.9
GR41	864.6

GR42	215.2
GR43	69.0
HR03	384.0
HU10	1.3
HU21	117.9
HU22	155.3
HU23	31.0
HU31	1.9
HU32	2.0
HU33	18.9
IE01	961.8
IE02	1439.1
ITC1	21.8
ITC3	33.9
ITC4	83.3
ITF1	234.7
ITF2	431.7
ITF3	953.1
ITF4	1655.8
ITF5	521.7
ITF6	915.0
ITG1	2683.9
ITG2	1005.5
ITH1	3.2
ITH3	1.3
ITH5	27.3
ITI1	117.2
ITI2	1.4
ITI3	4.8
ITI4	54.4
LT00	290.0
LU00	60.0
LV00	70.0
MK00	37.0
NL11	549.6
NL12	182.1
NL13	11.4
NL21	29.9
NL22	60.5
NL23	1151.5
NL31	10.5

NL32	696.5
NL33	386.5
NL34	410.1
NL41	135.5
NL42	17.3
NO02	3.7
NO03	0.5
NO04	160.2
NO05	292.2
NO06	224.9
NO07	179.2
PL11	211.9
PL12	160.6
PL21	0.5
PL22	1.3
PL31	26.5
PL32	463.1
PL33	2.0
PL34	123.2
PL41	614.4
PL42	1363.0
PL43	199.7
PL51	295.5
PL52	91.8
PL61	385.8
PL62	352.8
PL63	895.3
PT11	1506.3
PT15	210.1
PT16	2747.1
PT17	156.1
PT18	117.5
PT20	44.2
PT30	45.2
RO11	98.3
RO12	555.1
RO21	77.8
RO22	1708.8
RO31	221.4
RO32	113.8
RO41	0.2

RO42	147.6
SE11	61.2
SE12	220.6
SE21	417.9
SE22	410.9
SE23	457.6
SE31	485.4
SE32	510.4
SE33	465.3
SI01	0.5
SI02	2.5
SK02	3.0
UKC1	226.6
UKC2	224.8
UKD1	963.1
UKD3	0.5
UKD4	158.8
UKD7	105.4
UKE1	749.9
UKE2	42.5
UKE3	116.4
UKE4	9.4
UKF1	43.7
UKF2	135.9
UKF3	585.7
UKG2	0.5
UKH1	1154.2
UKH2	22.1
UKH3	249.6
UKI1	2.4
UKI2	14.5
UKJ1	16.3
UKJ2	0.9
UKJ3	0.6
UKJ4	1108.1
UKK1	35.4
UKK2	3.1
UKK3	114.0
UKK4	85.1
UKL1	1347.3
UKL2	128.6

UKM2	1143.1
UKM3	2182.1
UKM5	407.6
UKM6	1587.1
UKN0	598.1

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